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DIGITAL BILLBOARDS ADVERTISEMENTS' EFFECTS ON DRIVERS' PERFORMANCE AND ATTENTION

by
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AN ABSTRACT OF THE THESIS OF

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There is increasing interest in attempting to reduce the problem of driver distraction with the aim of decreasing the rate of road accidents and improving road traffic safety. Many existing work in the literature focuses on distraction caused from within the vehicle; however, the surrounding driving environment might also impair the driver's attention to the road. One of the main sources of outside distraction is the presence of digital billboard advertisements (DBAs) on roads and highways, especially as many of them are transitioning between different advertisements or are animated. The goal of this study was to analyze the effects of different types of DBAs on drivers' performance and attention. To this end, 100 students participated in a controlled driving simulator experiment in an urban environment. Measures of performance and attention were collected using eye tracking, EEG, simulator measures, and subjective evaluations. The different types of DBAs investigated were: static (single image advertisement), transitioning (two transitioning advertisements), and animated (short videos). The statistical analysis demonstrated that there were statistical differences in the effect of each format of DBA on drivers' performance (deviation from the center of the lane and reaction time), visual attention to the road (% fixations on the road, %fixation on DBAs, fixation duration on DBAs, and number of gazes on DBAs), and the theta band and beta band powers of the frontal cortex. Supervised and unsupervised machine learning models were used to detect driver distraction caused by DBAs. The results of this study will provide guidelines and recommendations for the better design and regulation of DBAs in order to minimize driver distraction. The results can also provide a building block for an in-vehicle intelligent system based on eye tracking and EEG that can detect distraction due to DBAs and warn the driver accordingly or activate self-driving mode.

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CHAPTER I

INTRODUCTION

According to the World Health Organization's (WHO) facts sheet updated May 2017, road accidents are the leading cause of death for people between the ages of 15 and 29 years old, and each year, an estimated number of 1.25 million human lives are lost due to car accidents. The World Health Organization (WHO) also predicts that in the year 2030, if no action plan is adopted for the current situation, car crashes will be ranked as the worldwide seventh leading cause of death [1].

The Lebanese Internal Security Forces (ISF) have estimated the number of occurrence of car accidents in Lebanon in the year 2016 to be 3647 causing 477 fatalities and 4879 injuries compared to 4907 car crashes, 657 fatalities, and 6463 injuries in 2014. The numbers of car accidents and victims have reached the lowest values compared to the past six years, probably due to the new traffic laws enforced n year 2015 and the increased awareness campaigns performed by governmental and non-governmental organizations dedicated to promoting road safety especially among teenagers who as shown in Figure 2 are the majority age group of the Lebanese victims of car accidents [2].

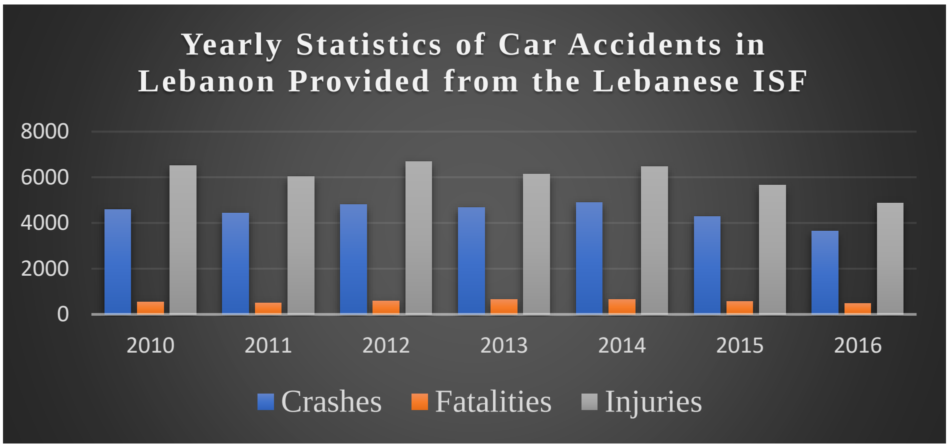


Figure 1. Statistics related to yearly car accidents in Lebanon from the year 2010 till 2016 [2]

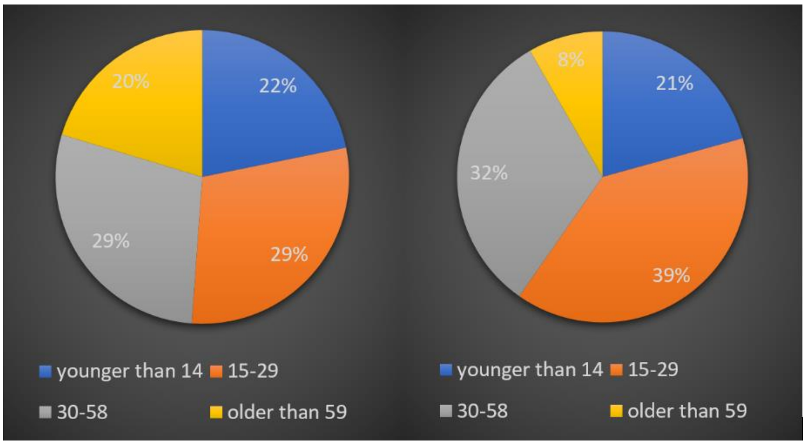


Figure 2. Percentage of fatalities (left) and injuries (right) due to car accidents in Lebanon according to age groups [2]

The causes for accidents can be categorized into three main classes: The driver, the vehicle, and the driving environment. The first class is related to mistakes committed by the driver such as being under the influence of alcohol or certain medications that would decrease the attention of the driver. Other examples would also include exceeding the speed limit and performing tasks that are distracting from the road such as mobile texting or web browsing. The second class involves the vehicle's breakdown or malfunction such as a flat tire or engine failure. The third class is associated with the outer environment of the vehicle such as the weather conditions, behavior of other vehicles or pedestrians, obstacles, damaged road, and distracting advertisements.

From the statistics gathered from the Lebanese Internal Security Forces (ISF), the main cause of reported car accidents in Lebanon is drivers' distraction, as shown in Figure 3 [2]. Following that is exceeding the speed limit and pedestrians violating crossing rules [2]. The National Highway Traffic Safety Administration (NHTSA) of the United States of America conducted a research study on causes of car accidents as well, and they reported that 78% of all car crash events involve a type of distraction from driving [3]. Results of such studies and statistics made drivers' distraction an interesting topic for governments and researchers in the field of transportation.

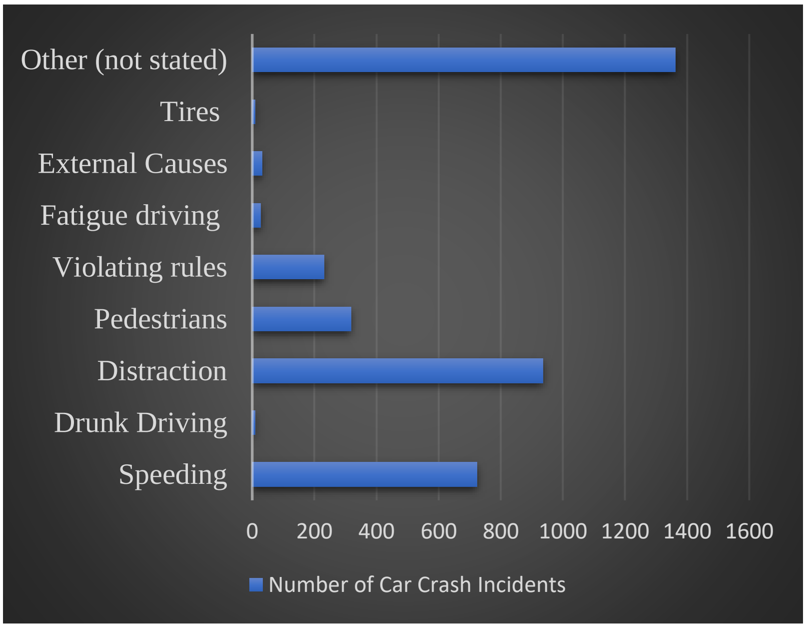


Figure 3. Causes of car crash incidents in Lebanon [2]

It is widely recognized that driver distraction can increase the risk of car accidents that would lead to devastating consequences for the driver, passengers, other vehicles, and pedestrians. It could lead to injuries, disabilities, and fatalities of the people in the vehicle and the surrounding environment. The International Organization for Standardization (ISO) defined driver distraction as paying attention to something that is irrelevant to the main task of driving in a manner that negatively affects driving performance [4].

The U.S. NHTSA has identified three types of driver distraction: visual distraction, manual distraction, and cognitive distraction [3]. Visual distraction is caused by having the eyes off the road, which could be due to looking at a mobile phone, pedestrians, or billboards. Manual distraction occurs when one or both hands are off the steering wheel to use the phone or music system. Finally, cognitive distraction occurs when attention is drawn to something other than the main driving task, even though the hands and eyes might be on the steering wheel or outside road, respectively. For example, a driver's attention might be focused on and their mind would then be consumed by that, rather than driving [3]. The causes of car accidents or poor driving performance could be a combination of different types of distraction.

Even though most studies focus on distractions caused from within the vehicle, distraction can also be caused by the outside environment [5, 6] Elements placed on the road such as road signs, variable message signs (VMS), advertisements, and large billboards, are designed to capture the attention of drivers,

One particularly concerning form of roadside advertisements are digital billboard advertisements (DBAs), which are electronic dynamic and interchangeable LED display advertisements. DBAs have started to be placed on several roads and highways in Lebanon. Figure 4 displays a DBA placed on a street in Beirut [7]. The danger with DBAs is that they can provide changing information, such as transitioning advertisements or videos that are known in the psychology literature to strongly capture attention [8].

Figure 4. An example of a digital billboard on a street in Beirut [7]

The aim of this study was to analyze the impairments that transitioning and animated DBAs might cause to drivers' performance and attention on the road as these types of billboards are increasing with no policies regulating them in some countries [9, 10, 11]. The results will aid in endorsing some recommendations for rules to regulate DBAs for the purpose of reducing the number of accidents caused by driver distraction which is believed to improve road safety. In addition, this paper focuses on developing a system that would use three types of inputs: driving performance, eye tracking and EEG data to detect drivers' distraction caused by DBAs using different machine learning algorithms. This system is expected to compliment semi-autonomous vehicles in the detection of drivers' distraction using inputs from the vehicle, eye tracking, and frontal cortex EEG for intervention, when needed, and switch to self-driving mode to reduce the probability of having a car accident.

The thesis is organized as follows. The literature review is presented in section two summarizing the related previous work. In section three, the methodology is subcategorized into the process of recruiting participants, the experimental design, the methodology for statistical analysis, and the machine learning decision making algorithms used. The results of the statistical analysis and machine learning models are presented in sections 6 and 7 respectively. The thesis is then concluded in section 8 with a summary of findings, contributions, limitations, and future work.

CHAPTER II

LITERATURE REVIEW

The International Organization for Standardization (ISO) defined driver distraction as paying attention to something that is unrelated to the task of driving in a way that impairs driving performance [4]. Some other definitions encountered in the literature are: “a shift in attention away from stimuli critical to safe driving toward stimuli that are not related to safe driving” [12]. “the temporary diversion of the driver’s attention towards a task, object, person, or thought that does not serve in the main task which is driving, which affects the driver’s attentiveness to the road and puts the driver and passengers at higher risk of encountering a car crash” [13]. “Distraction occurs when drivers divert their attention from driving task to a secondary activity instead such as having a phone conversation, texting, using the infotainment system, using the GPS, talking to the passenger, eating or drinking while driving.”[14].

When it comes to studying driver distraction, many studies are focusing on the effect of secondary tasks done by the driver while driving. Minor considerations are given to distraction caused by the driving environment which includes objects placed on the road such as digital billboard for advertisements [5, 6]. Billboard advertisements placed on roadsides have been increasing with few or none regulating policies for their locations, sizes, or how they are designed with no policies regulating them in some countries, including Lebanon [9, 10, 11].

In [5], Edquist et al. conducted experiments using simulated driving to study the impact of advertising billboards on drivers of different age groups and levels of experience using an eye tracking device. The result of this study showed that billboards interrupted the visual attention of drivers for road signs that it required them more time to follow road signs and therefore causing their driving performance to decline. Belyusar et al. conducted a field study to investigate the effect of digital billboards during naturalistic driving on a highway. It was shown that the duration of gazing towards the billboards was high and the rapid change from one advertisement to the other triggered the drivers to look at the billboards deviating their visual attention from the road [11]. Dukic et al [15] studied the effects of 4 digital billboards placed on 3-lane motorway in central Stockholm, Sweden during a trial period initiated by the Swedish Transport Administration. 41 drivers were recruited for the study of naturalized driving while being exposed to digital billboards. The results of the study showed that that drivers had extended gaze duration and increased number of visual fixations on digital billboards compared to road signs that were also present on the road. The Swedish Road Administration performed a questionnaire study which results posed problems due to brightness and visual clutter that drivers experienced. Therefore, the Swedish authorities decided to remove the digital billboards [15].

These studies point out the alarming flag that further research is needed to study the effect of digital billboards on driver distraction and proper regulations should be made based on the outcome of such study in order to alleviate any risk on drivers' and passengers' safety. Throughout the literature, there has been use of several types of sensors to study driver distraction. In this thesis, the vehicular monitor, eye tracker device, and EEG recorder will be used.

Sensors that account for vehicular data such as speed, steering wheel angle, gas pedal, brake pedal, longitudinal acceleration, and lateral acceleration are often used to describe the driving behavior or performance. A change in the driver's cognitive state can cause changes in his/her driving behavior. Many studies have confirmed through different experiments that non-distracted drivers steer their cars in a different way than when they are distracted; similar variations were noticed for speed, acceleration, lane position, and reaction time [16, 17]. In [14], a device called OBD II was used to measure all vehicular data at real time. Ryu et al. collected vehicular data during naturalistic driving using SCANeR Studio 2.16 and computer of Innosimulation Inc., in addition to other sensors to predict driver's state [18]. Chakraborty et al. use time series vehicular data, collected during simulated driving experiments, as features to predict driver's cognitive distraction using various machine learning techniques [19]. Liang

et al. built SVM models for the detection of drivers' cognitive distraction with driving behavior features exclusively [20]. Liang et al. and Zhang et al. found that including eye tracking metrics helped improve the accuracy for the detection of drivers' distraction and produced better results than using the driving behavior features solely. [20, 21]

Eye tracking devices are heavily used in the literature, which is understandable as the drivers' eye fixations hold valuable information when visual distraction is of interest to study. Fernández et al. discuss the importance of computer vision in developing visual based sensors to detect distraction in a flexible manner [22]. Eye tracking devices are almost solely used in analyzing the effect of road objects on driver's driving performance and his/her ability to notice these road objects as shown in the work of Topolšek et al. [6] where they have performed an experiment to study the ability of drivers to detect or be aware of roadside objects according to the location of these objects and their content. Yekhshatyan et al. combined both eye tracking data and vehicular parameters to detect driver distraction [23].

Studies similar to the work of Lin et al. [24][25] and Dehzangi et al. [14] suggest that features extracted from drivers' Electroencephalography (EEG), which are the theta and beta power band from the frontal cortex could serve as important characteristics to detect driver's inattention as these parameters have shown high correlation with driver distraction. The use of EEG for naturalistic driving might not be convenient or user-friendly to be incorporated in a commercial device, however, the information it provides serves well when analyzing the driver's his/her cognitive processing.

Many research groups have focused on multimodal detection of driver distraction where they have utilized multiple sensors to include in their system or algorithm. Putz et al. employed biomedical signals such as GSR, pulse, respiration, and EEG in simulated driving experiments where participants were asked to perform several tasks, with varied complexities, to use these signals in a machine learning classifier to predict the level of cognitive workload [26]. Yang et al. used various biological data (such as Heart Rate and blinking rate) and vehicular parameters to detect drowsiness, distraction, and high workload [27] [28]. In [29] a vehicular sensor, EEG, and FBSN (Full Body Sensor Network) as a part of a system built for real-time detection of driver distraction. Maglione et al. also analyzed drowsiness and workload during simulated driving using EEG, Heart Rate, and Eye Blinking Rate data [30].

Table 1. Previous Work on Driver Distraction and Billboards

Ref	Objective	Type of ads	Number of participants	Metrics	Methods	Results
[5]	Study the effects of billboards on driving performance according to age/ experience and type of billboard	. Static . Changeable Design: logo and tagline of a company	48	Driving performance Visual behavior	Time to change lanes and proportion of time fixating on the road were analyzed using ANOVA	Older drivers were slowest to change lanes overall, followed by novice drivers. The changeable billboards used did not show the expected consistently greater effects than the static billboards partly due to the simple design and the fact that it was programmed to change only once.
[11]	Investigate the effect of 2 digital billboards during driving on a highway	Changeable	123	Driving behavior Visual behavior	Number and length of glances and the % time glancing off the road were analyzed using ANOVA	a significant shift in the number and length of glances toward the billboards (right side) and an increased percentage of time glancing off road in the presence of the digital billboards.
[15]	Study the effect of 4 electronic billboards during day and night conditions.	Changeable	41	Driving behavior Visual behavior	Visual distraction was defined by dwelled for longer than 2 seconds at the billboard	Drivers had a significantly longer dwell time, a greater number of fixations, and longer maximum fixation duration when driving past an electronic billboard compared to other signs on the same road stretches. No differences were found for the factors day/night, and no effect was found for the driving behavior data.
Our Approach	Study effect of different formats of DBAs on driving behavior and attention	. Static .Transitioning . Animated	100	Driving behavior Visual behavior EEG	Analysis using ANOVA and machine learning approaches	

Table 2. Previous Work on Driver Distraction Detection Using Multi-sensors

Reference	Objective	Experiment	Sensors	Number of participants	Methods
24	Multimodal Recognition of Cognitive Workload for Multitasking in the Car	Simulated driving	GSR, pulse, respiration, and EEG	13	Machine learning classifier to predict the level of cognitive workload
25	Detection of drowsiness, distraction, and high workload while driving	Simulated driving	Heart Rate, blinking rate, and vehicular parameters	20	Statistical analysis
29	Towards real-time detection for driving distraction	Naturalistic driving	a vehicular sensor, EEG, and FBSN (Full Body Sensor Network)	5	Correlation Analysis
Our Approach	Study the impairments that DBAs might cause to drivers' performance and attention on the road.	Simulated driving	Driving behavior Visual behavior EEG	100	Analysis using ANOVA and machine learning approaches

CHAPTER III

DATA COLLECTION AND EXPERIMENTAL DESIGN

This section describes the methodology adopted in this study, from the recruitment of participants, to the instrumentation setup for the experiment, the design of the driving environment, the independent variables, dependent variables, and the procedure for the experiment.

A. Recruiting Participants

Upon obtaining the approval of The Institutional Review Board at the American University of Beirut (AUB), participants were informed about the research experiment though emails, flyers distributed across campus, and class announcements. Interested volunteers contacted the research team to schedule a time and date to perform the experiment. A screening interview before the start of the driving session is performed to make sure that the subject is qualified to participate. The inclusion criteria for participation are: an English literate, aged above 18, owns a driver's license, is an AUB student or employee, is in good physical and mental health, and is not taking medication such as sedatives and tranquilizers, muscle relaxants, and sleeping aids. The volunteers that did not meet the criteria were not allowed to participate in the study. The inclusion criteria were mentioned clearly in all the approaches mentioned for recruitment.

100 participants (41 females and 59 males) aged 18–44 years old (Average = 23.3, Standard Deviation= 4.38) took part in this study. 96 of these participants were students from different faculties (Maroun Semaan Faculty of Engineering (67), Faculty of Arts and Sciences (15), Olayan School of Business (7), Faculty of Medicine (3),

Faculty of Agriculture and Food Sciences (2), Hariri School of Nursing (1), Faculty of Health Sciences (1)) while 4 of the participants were employees (Management (3), Faculty(1)). 41 students were graduate students, while 55 were undergraduate students (38 seniors, 12 juniors, and 5 sophomores). The average driving experience for participants was 5.5 ±4.13 years with range= 0.5-26 years of driving experience.

B. Experiment Setup

The experiment was performed in the transportation lab of AUB using the DriveSafety™ driving simulation system. The driving simulation system consists of a partial ford focus cab with three projection screens at the front (shown in Figure 5) and the HyperDriving [31] authoring suite. From the driver's viewpoint, the three screens provide a field of view subtending an angle of approximately 180° horizontally. The projectors render visual imagery at 60 frames per second. It also includes three (right, left, middle) independently configurable rear view mirrors. An audio system from Logitech [32] is used to generate sounds to mimic the actual environment and give driver audible commands to execute tasks during the experiment. Data from the brake pedal, accelerator pedal, steering wheel angle, events of collisions (with other vehicles or pedestrians), and other driving behavior data were recorded at a rate of 60 Hz. Participants' visual behavior were recorded using the Eye Tracking Device, Fovio from Eye Tracker Incorporation [33] (Figure 6). The EPOC, 14 channel EEG headset wireless acquisition system, from Emotive [34] was used to record the electrical activity of the brain to be later on analyzed (Figure 7).

Figure 5. DriveSafety™ Driving Simulation System [31]

Figure 6. The Fovio Eye Tracker from Eye Tracker Incorporation [33]

Figure 7. The Emotive EPOC + Headset and electrodes [34]

C. Experiment Design

1. The independent variable

Since the concerned variable being tested is the format of the billboard, other variables that have the possibility to contribute to the distraction of drivers have been blocked, as explained in the following paragraphs. Blocking is a design technique used to improve the precision with which comparisons among the factors of interest are made. Blocking is used to eliminate the variability transmitted from nuisance factors that may influence the experimental response but are out of interest in this research study. [35]

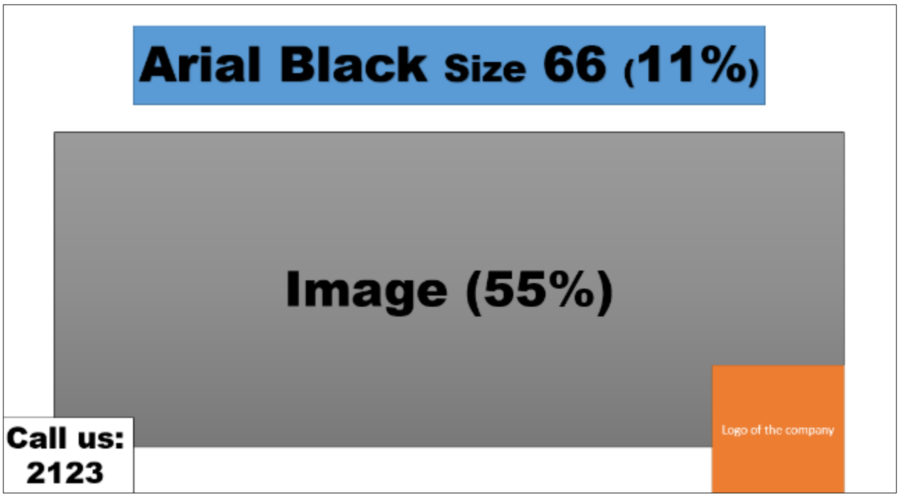


Figure 8. Sections of the DBAs: Text and Image surrounded by a white background

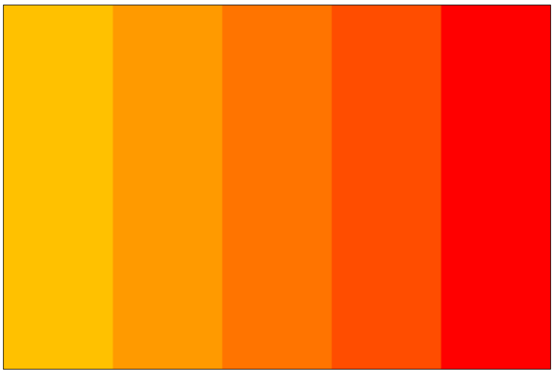


Figure 9. Red-Orange color palette used in DBAs

The size of all DBAs uploaded to the scenario were fixed at size 517 x 286 pixels. The percentage of text and image in all DBAs were also fixed such that the text section of all DBAs constituted around 11% the area of each DBA and the image section constituted around 55% of the area of the DBA as shown in figure 4 below. The same font and text sizes (Arial Black with 66 as font size) were used in all billboards. The contact info was within a white rectangle of 1.5"x 2.6" and included four random digits in black color, font: Arial Black, and 40 as font size.

The background color was fixed to “white color”. The colors used in all DBAs belonged to same color palette (Red-Orange) as shown in the figure 5 below. The logos of the companies were in black and white colors within a square of 2.5"x 2.5".

The locations of all the billboards were on the right sidewalk with equal distances between consecutive billboards. In addition, the appearance of DBAs was controlled by means of location triggers so that DBA started to become visible to participants when he/she was 140 m away from the DBA, as used in some of the literature (140m – 200m) [5,11,15]. This is to insure that the participant does not see multiple DBAs at the same time.

The total number of advertisements used in the experiment was 27 advertisements. 9 of which were placed at the intersection. There were 3 categories covered in the advertisements: cars, fashion, and food. The advertisements were also distributed equally among the three investigated formats: static, transitioning, and animated.

The first scenario is shown in figure 6. The other 2 scenarios involve the same road but with different orders of the type and format of DBAs. The scenario in which the participant drove through was chosen randomly. By properly randomizing the experiment, we also assist in averaging out the effects of extraneous factors that might be present, such as the first DBA that the participant sees, in each scenario a different format of DBA is used.

In total, there were 9 intersections with traffic lights: 4 of which were initially red and turned green and 5 of which were initially green and turned red.

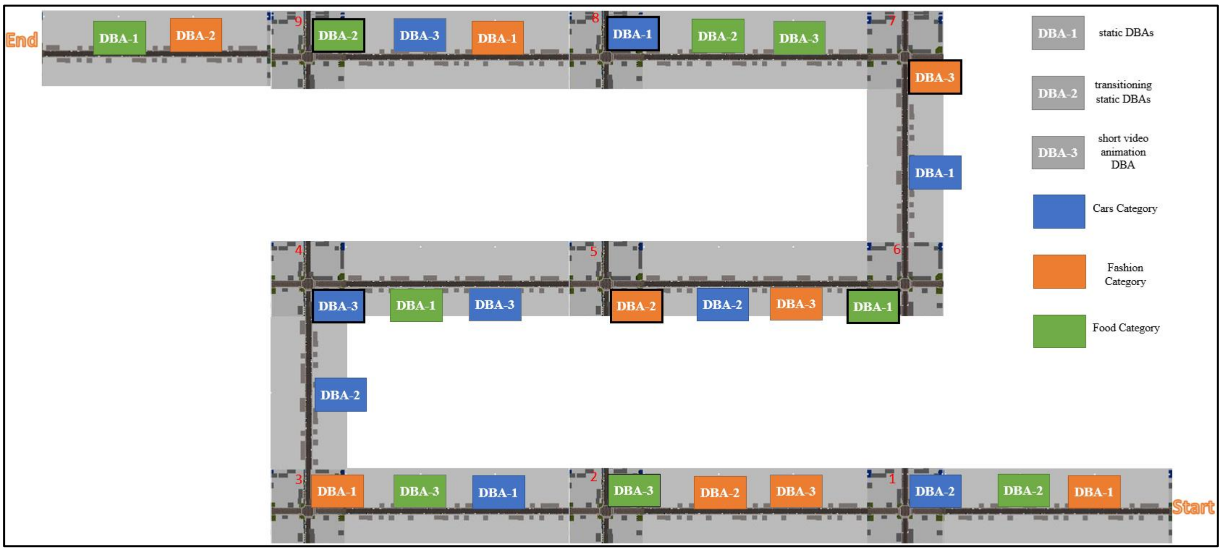


Figure 10. The roadmap of the drive with different types and formats of DBAs

Table 3. The three scenarios of the experiment

Intersections	**Scenario 1**	**Scenario 2**	**Scenario 3**
	DBA-1	DBA-2	DBA-3
	DBA-2	DBA-3	DBA-1
Intersection 1	**DBA-2**	**DBA-3**	**DBA-1**
	DBA-3	DBA-1	DBA-2
	DBA-2	DBA-3	DBA-1
Intersection 2	**DBA-3**	**DBA-1**	**DBA-2**
	DBA-1	DBA-2	DBA-3
	DBA-3	DBA-1	DBA-2
Intersection 3	**DBA-1**	**DBA-2**	**DBA-3**
	DBA-2	DBA-3	DBA-1
Intersection 4	**DBA-3**	**DBA-1**	**DBA-2**
	DBA-1	DBA-2	DBA-3
	DBA-3	DBA-1	DBA-2
Intersection 5	**DBA-2**	**DBA-3**	**DBA-1**
	DBA-2	DBA-3	DBA-1
	DBA-3	DBA-2	DBA-1
Intersection 6	**DBA-1**	**DBA-2**	**DBA-3**
	DBA-1	DBA-2	DBA-3
Intersection 7	**DBA-3**	**DBA-2**	**DBA-1**
	DBA-3	DBA-2	DBA-1
	DBA-2	DBA-3	DBA-1
Intersection 8	**DBA-1**	**DBA-2**	**DBA-3**
	DBA-1	DBA-2	DBA-3
	DBA-3	DBA-1	DBA-2
Intersection 9	**DBA-2**	**DBA-3**	**DBA-1**
	DBA-2	DBA-3	DBA-1
	DBA-1	DBA-2	DBA-3

The pre-trigger is the state before the appearance of the DBA therefor, the DBA is not visible to the driver. Recording the pre-trigger is important to consider the baseline when the DBAs are not present to compare with the cases of the presence of different DBAs.

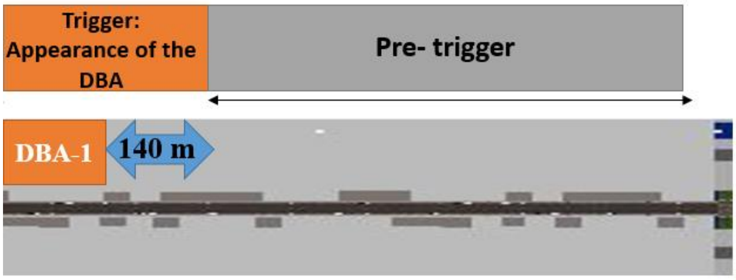


Figure 11. For each DBA, three phases are involved: Pre-trigger, Trigger, and Post-trigger

2. The Dependent Variables

The dependent variables in this experiment include averaged data from driving performance measures, eye tracking data, and electroencephalogram (EEG) band power.

a. Driving Performance and Vehicular Parameters

The data collected from the driver simulator include the vehicular parameters such as average speed (meters/ second), average acceleration/ deceleration (meters/ second2), average deviation from the center of the lane (meters), average reaction time to traffic lights (seconds) serve as dependent variables.

Table 4. The Driving Performance Metrics

Driving Performance Metrics	**Unit**	**Definition**
Average speed	Meters / second	Average speed of the driver recorded continuously throughout the whole experiment.
Average acceleration/ deceleration	Meters/ second^2	Average acceleration/deceleration of the driver recorded continuously throughout the whole experiment.

Average deviation from the center of the lane Position	Meters	Average driver distance away from the center of the lane.
Average reaction time to traffic lights at the intersection	Seconds	Average reaction time needed for drivers to react to traffic lights. So if the traffic light was initially red and turned green, the reaction time is the time recorded from the change of the traffic light to green till the time the driver starts to accelerate. Whereas, if the traffic light was initially green and turned red, the reaction time is the delay in decelerating once the traffic light turns red.

b. Visual Behavior

DBAs are expected to cause interference with the visual fixation on the road. Thus the visual behavior of participants while driving in the simulated environment is recorded using the Eye tracker device. The parameters taken into consideration are shown in the table below.

Table 5. The Eye Tracking Metrics

Visual Behavior Metrics	**Unit**	**Definition**
Average % of Fixations on Road	%	Average percentage of instances that the eye momentarily stops within the region of road.

Average % of Fixations on DBA	%	Average percentage of instances that the eye momentarily stops within the region of DBA
Average Fixation Duration in DBA	Seconds	Average time of visual fixation in the DBA.
Average Number of Gazes on the DBA	Number	The number of times the subject looks at the DBA during the presence of the DBA. This metric measures the number of times the driver's visual focus moves into the area that is covered by the DBA. If the driver, for example, was initially looking at something other than the DBA then looks at the DBA and then looks back at the road then looks again at the same DBA, the number of gazes on the DBA recorded would be equal to 2. This metric serves as an indication of how many times the DBA disturbs the driver's attention to the road and their interest to look again at the DBA if the number of gazes exceeded one. This is probably because only one gaze at the DBA was not satisfactory to the driver.

c. EEG Band Power

While the impairment of visual attention caused by DBAs was examined using parameters of visual behavior captured by the eye tracker device, the interference with cognitive processing is examined by analyzing the EEG band power of the driver. The MATLAB software from MathWorks [36] was utilized for EEG preprocessing and analysis.

EEG recorded using the EPOC headset first underwent pre-processing which involves noise and artifact filtering. The filter used is a low pass filter with cutoff frequency of 50 Hz. A high-pass filter with a cut-off frequency of 0.5 Hz was used to eliminate the unwanted DC drift. The 14 channel EEG signals were then divided into 20-second epochs/ segments.

Pre-processing was followed by spectral analysis as the theta (4 –7 Hz) and beta (16–31 Hz) power bands from the frontal cortex are of interest since it has been shown in previous work to be related to distraction. The power spectral density of each segment of EEG was made to record the power of the all the band powers (theta, alpha, beta, and gamma) were considered as features from the EEG of the driver.

Table 6. The EEG Metrics

EEG Metrics	Unit	Definition	Relevance to the main objective
Theta band power	dB	(4-8 Hz)	Studies similar to the work of Lin et al. [24][25] and Dehzangi et al. [29] suggest that features extracted from drivers' EEG, which are the theta (high) and beta (low) power band from the frontal cortex could serve as important characteristics to detect driver's inattention as these parameters have shown high correlation with driver distraction.
Alpha band power	dB	(8-12 Hz)	The prominent EEG wave pattern of an awake relaxed adult whose eyes are closed is the alpha rhythm. This rhythm is generally associated with decreased levels of attention, relaxation, and meditation states. When people are in an attentive state, or are

			thinking hard about something, the alpha rhythm is replaced by smaller amplitude, faster oscillations. [37]
Beta band power	dB	(12-25 Hz)	Low beta band power is indicative of distraction [24, 25, 29]
Gamma band power	dB	(25-45 Hz)	A decrease in gamma-band activity may be associated with cognitive decline, especially when related to the theta band; however, this has not been proven for use as a clinical diagnostic measurement. [37]

D. Experiment Procedure

A screening interview was first performed with the participant to make sure that they were eligible to participate in the experiment. This interview included questions related to their medical profile and their driving records. Once it was confirmed that the participant was eligible to participate, he/she was given an information sheet which stated the objective of this experiment was to study their driving behavior. Subjects were not aware that their distraction was assessed according to the different types of DBAs. Moreover, the presence of the different types of DBAs was not mentioned in the information sheet that the participants signed prior to the experiment because knowing that may affect the overall results of the experiment. After agreeing to participate, the volunteers filled a consent form and a demographics survey to record information about his/her age, gender, and years of experience in driving while keeping their profiles as anonymous. The participant was then seated in the driver's seat of the partial cab and was introduced to the driving simulator and instructed to obey traffic lights signs and follow the audio instructions to turn left or right at intersections. They were also instructed to inform the experimenter if they felt dizzy or nauseous at any time during the experiment and that they can withdraw from the experiment at any time without being penalized. The participant drove through a track similar to the actual experiment, yet much shorter in duration (10 minutes), in order to get accustomed to the vehicle's control system. This test drive also included 9 DBAs different from what were used in the actual drive but following the same rules in the design stated in section 3.3.1.

The participant then underwent the procedure of EEG electrodes placement on his/her scalp and any required procedure of calibration of the EEG instrumentation and Eye Tracker device. Once everything is in place, and all the sensors were attached properly, the participant drove through the actual experiment.

Once the actual experiment began, the experimenter stayed close, in case the participant for some reason experiences any discomfort. The driving experiment took around 20 minutes to complete.

After the driving experiment, the participants were asked to fill a post-experiment survey asking them various question among which are: which advertisements they remember and their assessment of their performance and attention throughout each section of their drive.

CHAPTER IV

STATISTICAL ANALYSIS

The first step trying to make sense of the data collected is to perform statistical analysis. The one-way repeated measures analysis of variance (ANOVA) [38] is performed using the IBM SPSS Statistics Software package [39] to learn if there are statistically significant differences between the means of data collected in the four different cases that all the participants went though. These cases are: the absence of DBAs, the presence of static DBAs, the presence of transitioning DBAs, and the presence of animated DBAs.

Before performing the one way repeated measures ANOVA, the data had to comply with five assumptions, otherwise, some modifications were made before proceeding.

The first assumption is that the data has a continuous dependent variable. For example, the average speed (m/sec), average fixation duration (sec), and average theta power band form the EEG (dB) are measured continuously.

The second assumption is that the data has a within-subjects factor which is of more than two categories. In this analysis there are four categories which relate to the absence or presence of DBAs and their types.

The third assumption is that the data does not have significant outliers in any level of the within-subjects factor. If outliers are significant, they should be removed from the data.

The fourth assumption is that the dependent variable is approximately normally distributed for each level of the within-subjects factor. Otherwise, transformations should be applied to make the data closer to being normally distributed. If transformations fail, non-parametric tests such as Friedman’s test [40].

The fifth assumption is of sphericity which states that that the differences between the levels of the within-subjects factor (Types of DBAs) have equal variances. When this assumption is violated, an adjustment needs to be made (to the degrees of freedom) so that the test still returns a valid result (i.e., returns the correct p-value). Mauchly's test of sphericity [41] is performed to make sure if sphericity is violated or not. If sphericity is found to be violated, Greenhouse-Geisser correction [42] was applied to proceed with the one way repeated measures ANOVA.

The below flow chart explains the process of the assumptions and the related adjustments to finally obtain the pairwise comparisons in the statistical analysis section of this thesis.

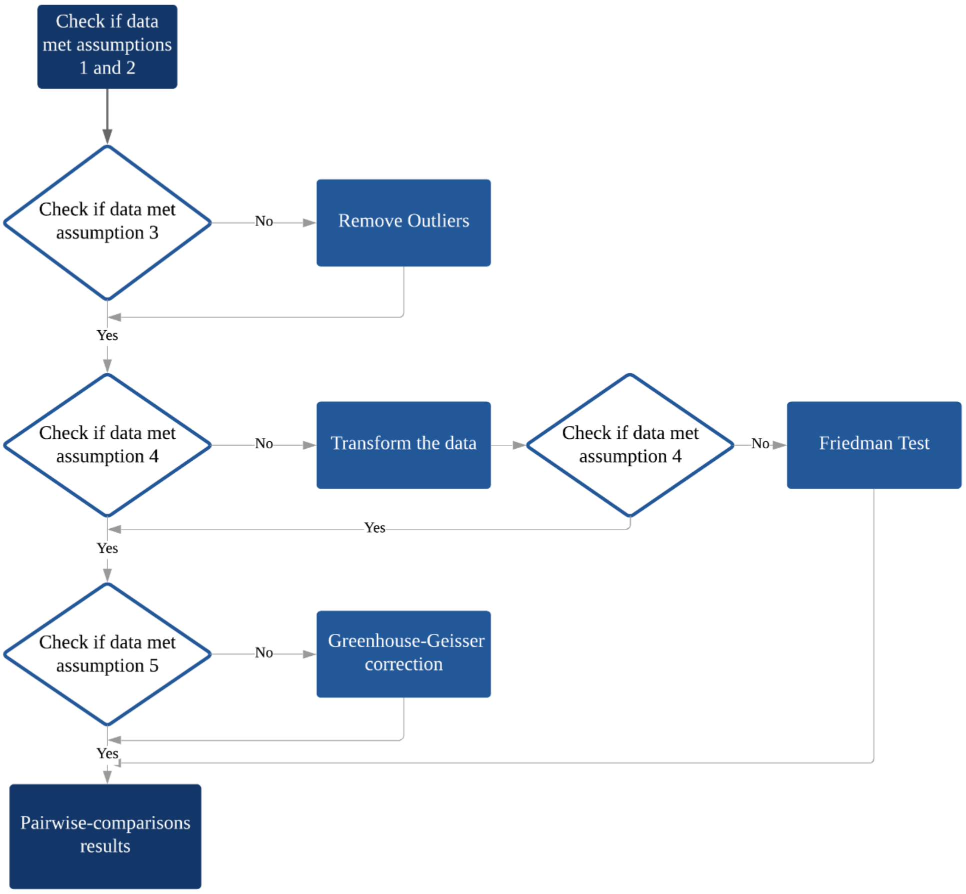


Figure 12. Flowchart of the one way repeated measures ANOVA and its associated adjustments

CHAPTER V

MACHINE LEARNING ANALYSIS

The data were separated according to the format of DBAs. Machine learning models were used to binary classify between distracted and not distracted for the 3 types of data: data of static DBAs, data of transitioning DBAs, data of animated DBAs. A total of 13 features (shown in tables 4, 5, and 6) were selected in developing the machine learning models. A clustering study was also performed.

A. Principle Component Analysis

Principal component analysis (PCA) is a statistical method that uses an orthogonal transformation to convert a dataset which might hold correlated features into a set of values of linearly uncorrelated variables referred to as principal components. These principal components are a linear combination of the variables in the initial dataset and are orthogonal to each other. Therefore, there is no redundant information. The number of principal components is equal to the number of variables in the initial dataset. The first principle component explains the data most by explaining the most significant variance. The variance of the principal components decreases from the first principle component to the p^{th} principle component with p being the number of features. [43]

B. Statistical Labeling Approach (L1, L2, L3)

Many of the research revolving around drivers' distraction and detection of drivers' distraction have used subjective measures or statistical methods to label the collected data. One of the statistical approach in labeling data uses the upper quartile of one feature that is indicative of distraction and labeling samples with values greater or equal to the upper quartile of this feature as “distracted” and the remainder as “not distracted”[20, 44].

L1 refers to the method of labeling the data based on driving performance where the values equal to the upper quartile of all the average deviation from the center of the lane of each participant, within the same format of DBA, is labeled as “distracted” while the remainder is labeled as “not distracted.” The features used in the L1 labeling approach are all the 13 features except the average deviation from the center of the lane, ending up with the 12 features: The 16 features used include: average speed, average acceleration/deceleration, average reaction to traffic lights, average % fixations on the road, average % fixations on DBA, average fixation duration on DBA, average number of gaze, average EEG theta band power, average EEG alpha band power, average EEG low beta band power, average EEG high beta band power, and the average EEG gamma band power.

L2 refers to the method of labeling the data based on eye tracking data where the values equal to the upper quartile of all the average fixation duration on DBA of each participant, within the same format of DBA, is labeled as “distracted” while the remainder is labeled as “not distracted.” The features used in the L2 labeling approach are all the 13 features except the average fixation duration on the DBA, ending up with 12 features: average speed, average acceleration/deceleration, average deviation from the center of the lane, average reaction to traffic lights, average % fixations on the road, average % fixations on DBA, average number of gaze, average EEG theta band power, average EEG alpha band power, average EEG low beta band power, average EEG high beta band power, and average EEG gamma band power.

Moreover, L3 refers to the method of labeling the data based on EEG band power data where the values equal to the upper quartile of all theta band power of each participant, within the same format of DBA is labeled, as “distracted” while the remainder is labeled as “not distracted.” The features used in the L3 labeling approach are all the 13 features except the average EEG theta band power, ending up with 12 features: average speed, average acceleration/deceleration, average deviation from the center of the lane, average reaction to traffic lights, average % fixations on the road, average % fixations on DBA, average fixation duration on DBA, average number of gaze, average EEG alpha band power, average EEG low beta band power, average EEG high beta band power, and the average EEG gamma band power.

C. Labeling through Machine Learning Clustering (L4)

Cluster analysis is an unsupervised learning approach used for unlabeled data to identify distinct groups or clusters in data that is unlabeled. Using this method identifies clusters where data points of the same cluster, share similar or comparable characteristics for “distracted” and “not distracted”. The features used in L4 approach are all the 13 features: average speed, average acceleration/deceleration, average deviation from the center of the lane, average reaction to traffic lights, average % fixations on the road, average % fixations on DBA, average fixation duration on DBA, average number of gaze, average EEG theta band power, average EEG alpha band power, average EEG low beta band power, average EEG high beta band power, and the average EEG gamma band power.

1. K-Means Clustering

K-means clustering is a popular method for cluster analysis in machine learning. The goal of k-means clustering is to partition n data points into k clusters (where k is known) in which each sample belongs to the cluster with the closest mean. The standard algorithm uses an iterative refinement approach.

Given an initial set of k means $m_1^{(1)},\ldots,m_k^{(1)}$, the algorithm proceeds by alternating between the two below steps [45]:

Step (1) Assignment step: each sample is assigned to the cluster whose mean has the least squared Euclidean distance.

$$S_i^{(t)} = \left\{x_p : \left\|x_p - m_i^{(t)}\right\|^2 \leq x_p : \left\|x_p - m_j^{(t)}\right\|^2 \ \forall j, 1 \leq j \leq k\right\}$$

Where each x_p is assigned to exactly one $S^{(t)}$, even if it could be assigned to two or more of them.

Step (2) Update: Calculate the new centroids of the data points in the new clusters

$$m_i^{(t+1)} = \frac{1}{\left|S_i^{(t)}\right|} \sum_{x_j \in S_i^{(t)}} x_j$$

The algorithm will converge once the assignments no longer change.

2. K-Medoids

The k-medoids algorithm is a clustering algorithm that resembles the k-means algorithm. Both the k-means and k-medoids algorithms are breaking the dataset up into clusters. K-means aims to minimize the total squared error, while k-medoids aims to minimize the sum of dissimilarities between data points that are labeled to be in a cluster and a point designated as the center of that cluster. The standard algorithm for k-medoid clustering is the Partitioning Around Medoids (PAM) algorithm and is as the following steps: Step (1) Initialization by randomly selecting *k* of the *n* data points as the medoids. Step (2) Assigning each data point to the closest medoid. Step (3) update the values for each medoid *m* and for each data point *o* that is associated to *m* swap *m* and *o* and calculate the total cost of the configuration. Choose the medoid *o* with the lowest cost of the configuration. Continue alternating steps (2) and (3) until conversion. [46, 47]

The k-medoids chooses datapoints as centers, in contrary to k-means. K-medoids clustering is more robust to noises and outliers than the K-means clustering algorithm which is sensitive to outliers, due to the fact that extreme values affect the mean easily. [46, 47]

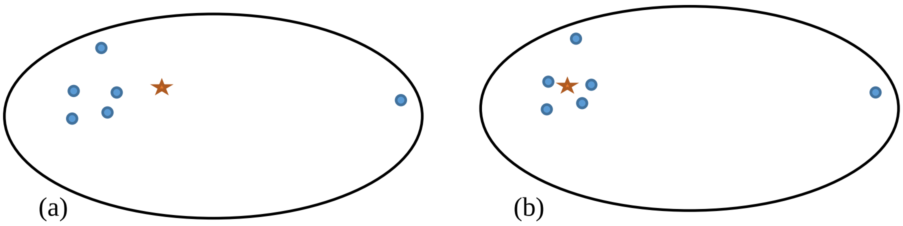


Figure 13. The difference in assigning the center of cluster in (a) K-means and (b) K-medoids

3. Fuzzy C Means

The FCM algorithm aims to partition a finite collection of *n* data points $X = \{x_1, \ldots, x_n\}$ into a number of *c* fuzzy clusters with respect to some criterion. Given a finite set of data, the algorithm outputs a number of *c* cluster centers $C = \{c_1, \ldots, c_c\}$ and a partition matrix $W = w_{ij} \in [0,1], i = 1, \ldots, n,\ j = 1 \ldots, c$ where each element, w_{ij}, tells the degree to which element, x_i, belongs to cluster c_j. The FCM algorithm aims to minimize the objective function: [48]

$$\arg min \sum_{i=1}^{n} \sum_{j=1}^{c} w_{ij}^{m} \left\| x_i - c_j \right\|^2 \text{, where: } w_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|} \right)^{\frac{2}{m-1}}}$$

D. Supervised Machine Learning

1. Support Vector Machine

Support vectors machine (SVM) is a supervised machine learning method used for classification and regression applications by finding a hyperplane in an N-dimensional space that distinctly classifies the data points with maximum marginal distances that contribute to more confidence in classifying new data points. Suppose a training dataset is available (with labeled data) $(x_1, y_1), \dots, (x_n, y_n)$, where y_i are either 1 if belonging to class 1 or -1 if belonging to class 2.

A separating hyperplane can be expressed as $\vec{w}.\vec{x} - b = 0$, with $\vec{w}$ as a normal vector to the hyperplane.

Non-linear SVM is used for linearly inseparable data. It is identical to the above algorithm, but with every dot product substituted with a nonlinear kernel function to better fit the maximum margin hyperplane in a transformed feature space. [49]

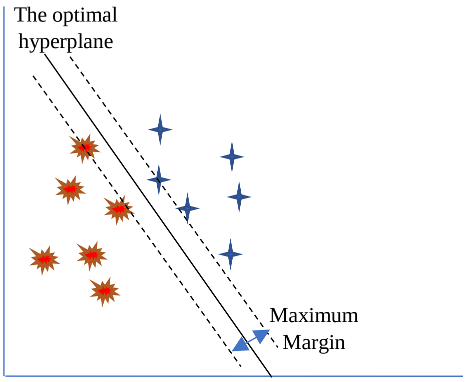


Figure 14. SVM Example [49]

2. Decision trees

Decision trees are used in machine learning for both classification and regression applications. They have a structure that resemble a flow chart mechanism, where each internal node represents an assessment on a feature, each branch denotes the result of the assessment, and each terminal node outputs the label. Constructing a decision tree learning algorithm works from top to bottom in the sense of selecting a feature that would best split to the rest of the features. The decision of the how the architecture of the tree should be is achieved the gini impurity or using or information gain. [50]

The gini impurity is an assessment of the likelihood of a wrong classification of a new instance of a random variable, if that new instance were randomly classified according to the distribution of class labels from the data set. To calculate the Gini impurity for a set of data point with *J* classes, and *pi* are the items that belong to class *i*. [50]

$$I_G(p) = \sum_{i=1}^{J} p_i \sum_{k \neq i} p_i = \sum_{i=1}^{J} p_i(1 - p_i)$$

$$= \sum_{i=1}^{J} (p_i - p_i^2) = \sum_{i=1}^{J} p_i - \sum_{i=1}^{J} p_i^2 = 1 - \sum_{i=1}^{J} p_i^2$$

Information gain is a measure of how much “information” a certain feature can provide about a class. The decision trees algorithm tries to maximize information gain making the attribute with the highest information gain be split first. [50]

$$IG(T, a) = H(T) - H(T|a) = -\sum_{i=1}^{J} p_i log_2 p_i - \sum_{a} p(a) \sum_{i=1}^{J} -\Pr(i|a) log_2 \Pr(i|a)$$

Where, $H(T)$ is the Entropy of parent and $H(T|a)$ is the weighted sum of Entropy of children. [50]

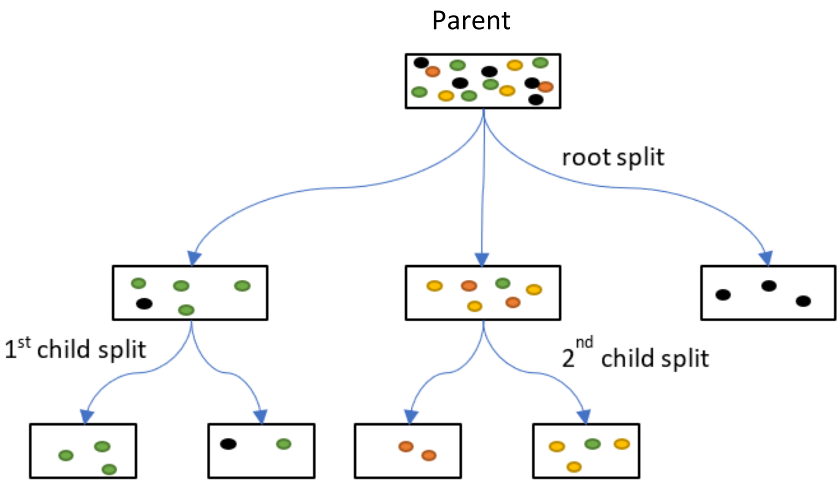


Figure 15. Decision tree example

*[50]**3. K nearest neighbors (KNN)***

KNN algorithm is a pattern recognition, non-parametric method used also for both classification and regression. The KNN algorithm operates by storing the previous known cases and classifies new instances based on a similarity measure of distance functions (such as Euclidean, Manhattan, and Minkowski). After obtaining the K nearest neighbors, a simple majority of these KNNs are selected in the prediction of the new instance. The example below demonstrates how KNN algorithm works as we change K. The point in question is the green point. [51, 52]

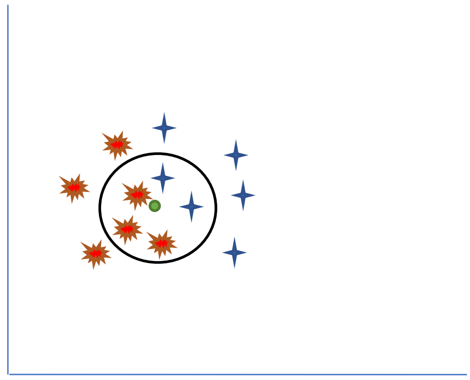


Figure 16. KNN Classification example [52]

Based on 1-nearest neighbor, the data point in question is classifies as red. Whereas, based on 2-nearest neighbor, KNN will not be able to classify the point since the second nearest point is blue. As for setting K to 5 leads to classifying the point in question to red as the number of votes for the red are 3 and the number of votes for blue are 2. [51, 52]

E. Feature Importance

The function predictorImportance in MATLAB [36] takes the features and labels as inputs to compute estimates of feature importance for decision tree model by adding the changes in the mean squared error (MSE) of the splits on every feature and dividing that sum by the number of branch nodes in the decision tree model. If the tree has no surrogate splits, this sum is taken over best splits found at each branch node. If the tree has surrogate splits, this sum is taken over all splits at each branch node including surrogate splits. The value of importance has one element for each input feature in the data used to train this tree. At each node, MSE is estimated as node error weighted by the node probability. Variable importance associated with this split is calculated as the difference between MSE for the parent node and the total MSE for the resulting two children.

If the feature is found to have high importance, the model is said to be very dependent on that feature and that this particular feature plays an important role in the model's prediction of "distracted" and "not distracted". Thus, the model could be considered to be biased towards that feature. However if the feature shows low importance (~ 0), the model dependence on that feature is low or is nonexistent and hence the model is considered not biased towards that feature. [36]

The 16 features considered were: average speed, average acceleration/deceleration, average deviation from the center of the lane, average reaction to traffic lights, average % fixations on the road, average % fixations on DBA, average fixation duration on DBA, average number of gaze, average EEG theta band power, average EEG alpha band power, average EEG low beta band power, average EEG high beta band power, average EEG gamma band power, gender, age in years, and years of experience in driving. While the labeling were based on the L4 method mentioned in section 5.3.

CHAPTER VI

RESULTS OF STATISTICAL ANALYSIS

A. Driving Performance Statistical Analysis Results

1. Average Speed Statistical Analysis Results

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in average speed in the driving performance of the 100 participants in four different cases: absence of DBA, exposure to static DBAs, exposure to transitioning DBAs, and exposure to animated DBAs. There were relatively few outliers and the data was normally distributed at each time point, as assessed by boxplot and Shapiro-Wilk test ($p > .05$), respectively. The assumption of sphericity was not met, as assessed by Mauchly's test of sphericity, $\chi2$ (2) = 53.099, $p < 0.0005$. Epsilon (ε) was 0.742, as calculated according to Greenhouse & Geisser (1959), and was used to correct the one-way repeated measures ANOVA. The exercise intervention did not elicit statistically significant changes in average speed, F (2.226, 220.352) = 1.750, $p = .172$, $\eta2 = .017$.

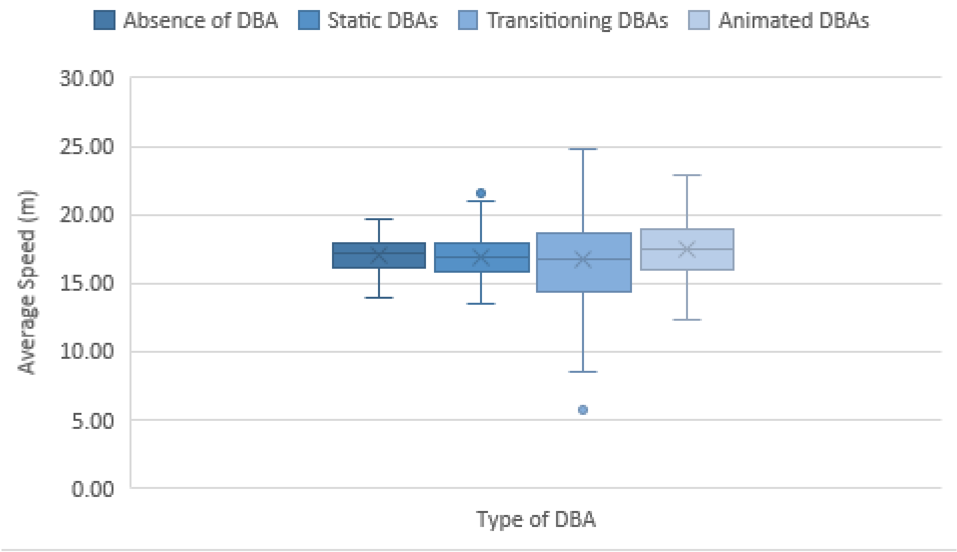


Figure 17. The average speed (m/s) with the absence and presence of the three types of DBAs on the road

2. Average Acceleration/ Deceleration

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the average acceleration and deceleration in the driving performance of the 100 participants in four different cases mentioned previously. There were relatively few outliers and the data was normally distributed at each time point, as assessed by boxplot and Shapiro-Wilk test ($p > .05$), respectively. The assumption of sphericity had not been violated, as assessed by Mauchly's test of sphericity, $\chi 2$ (2) = 5730, p =0.333. The exercise intervention did not elicit statistically significant changes in average speed, F (3, 297) = 1.849, p=0.138, $\eta 2$ = .018.

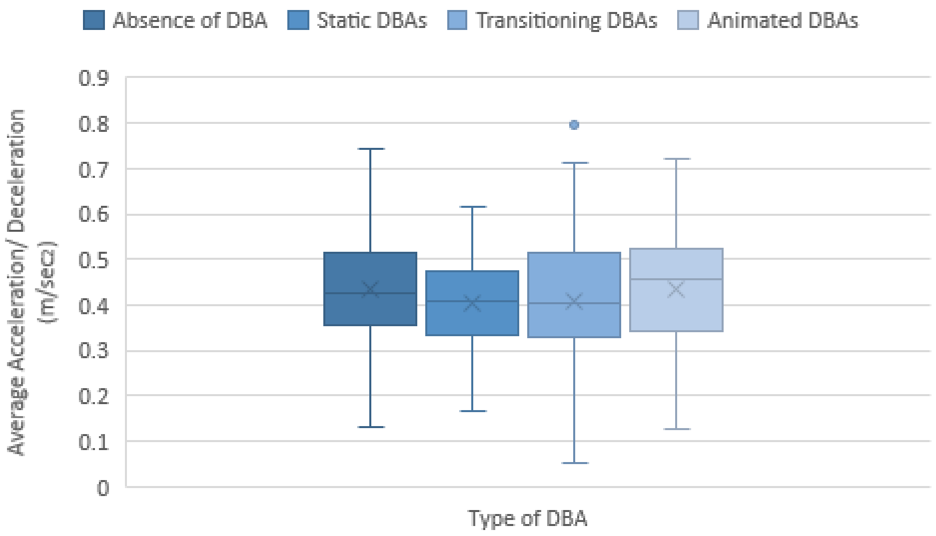


Figure 18. The average acceleration/deceleration (m/sec2) with the absence and presence of the three types of DBAs on the road

3. Average Deviation from the Center of the Lane

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the lane position in the driving performance of the 100 participants in thefour different cases mentioned previously. There were relatively few outliers and the data was normally distributed at each time point, as assessed by boxplot and Shapiro-Wilk test ($p > .05$), respectively. the assumption of sphericity had not been violated, as assessed by Mauchly's test of sphericity, $\chi2(2) = 8.602$, $p = 0.126$. The deviation from the center of the lane was statistically significantly different at the exposure of the different types of DBAs, $F(3, 297) = 1477.180$, $p < .0005$, $\eta2 = .937$.

The average deviation from the lane with the absence of DBA changed from 0.21 ± 0.06 to 0.3 ± 0.06 when exposed to static DBAs, to 0.54 ± 0.04 when exposed to transitioning DBAs, to 0.67 ± 0.05 when exposed to animated DBAs a statistically significant difference of 0.09 (95% CI,0.114 to 0.067), $p < .0005$, 0.457 (95% CI,-0.479to -0.435), $p < .0005$, respectively.

The average deviation from the lane when exposed to static DBAs changed from 0.3 ± 0.06, to 0.54 ±0.04 when exposed to transitioning DBAs, and to 0.67 ±0.05 when exposed to animated DBAs a statistically significant difference of 0.235 (95% CI,0.254 to 0.216), $p < .0005$, 0.367 (95% CI, 0.388 to 0.346), $p < .0005$, respectively.

The average deviation from the lane when exposed to transitioning DBAs changed from to 0.54 ±0.04 to 0.67 ±0.05 when exposed to animated DBAs a statistically significant difference of 0.132 (95% CI,0.151 to 0.113), $p < .0005$.

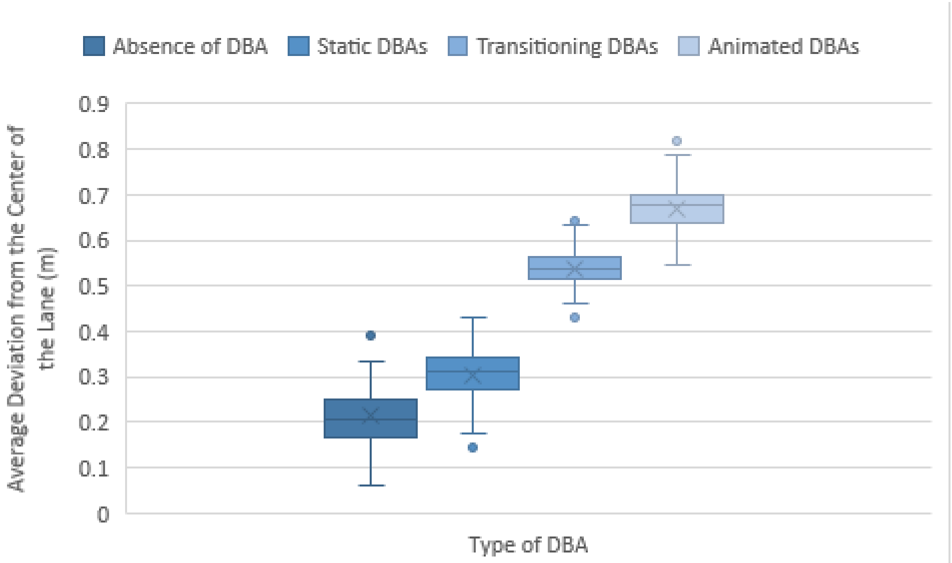


Figure 19. The average deviation from the center of the lane with the absence and presence of the three types of DBAs on the road.

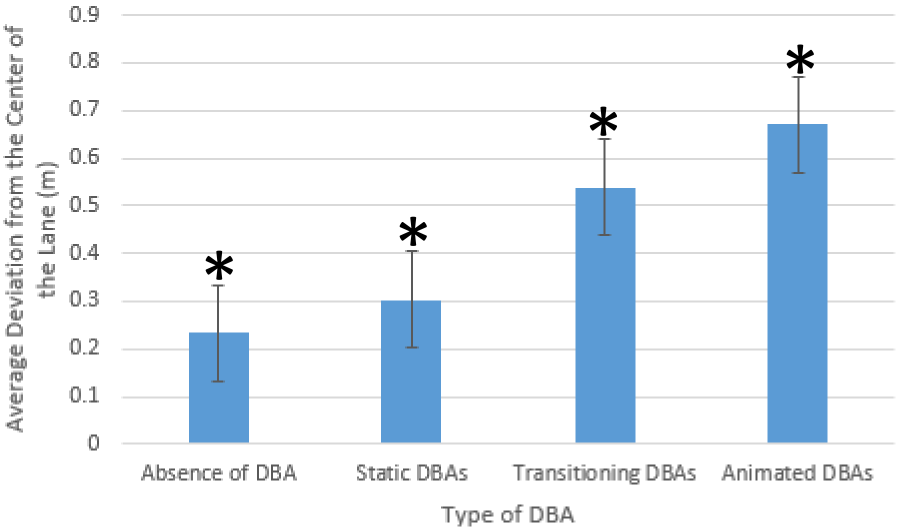


Figure 20. The statistically significant differences in the deviation from the center of the lane data

4. Average Reaction Time to Traffic Lights

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the reaction time to the traffic lights in the driving performance of the 100 participants in the four different cases mentioned previously. There were relatively few outliers and the data was normally distributed at each time point, as assessed by boxplot and Shapiro-Wilk test ($p > .05$), respectively. The assumption of sphericity had been violated, as assessed by Mauchly's test of sphericity, $\chi2(2) = 16.698$, $p = 0.005$. Therefore, a Greenhouse-Geisser correction was applied ($\varepsilon = 0.897$). The reaction time to traffic lights was found statistically significantly different at the absence and exposure of the different types of DBAs, F (2.692, 266.484) =31.196, $p < .0005$, partial $\eta2 = .240$.

The average reaction time to traffic lights increased from 1.36 ± 0.35 seconds when not exposed to DBAs to 1.65 ± 0.33 seconds when exposed to transitioning DBAs, and 1.9 ± 0.47 seconds when exposed to animated DBAs, a statistically significant increase of 0.283 (95% CI,0.413 to 0.125), $p < .0005$ and 0.539 (95% CI,0.690 to 0.389), $p < .0005$, respectively.

The average reaction time to traffic lights increased from 1.5± 0.48 seconds when exposed to static DBAs to 1.9± 0.47 seconds when exposed to animated DBAs, a statistically significant increase of 0.399 (95% CI,0.585 to 0.213), $p < .0005$.

The average reaction time to traffic lights increased from 1.65 ± 0.33 seconds when exposed to transitioning DBAs to 1.9± 0.47 seconds when exposed to animated DBAs, a statistically significant increase of 0.257 (95% CI,0.405 to 0.108), $p < .0005$.

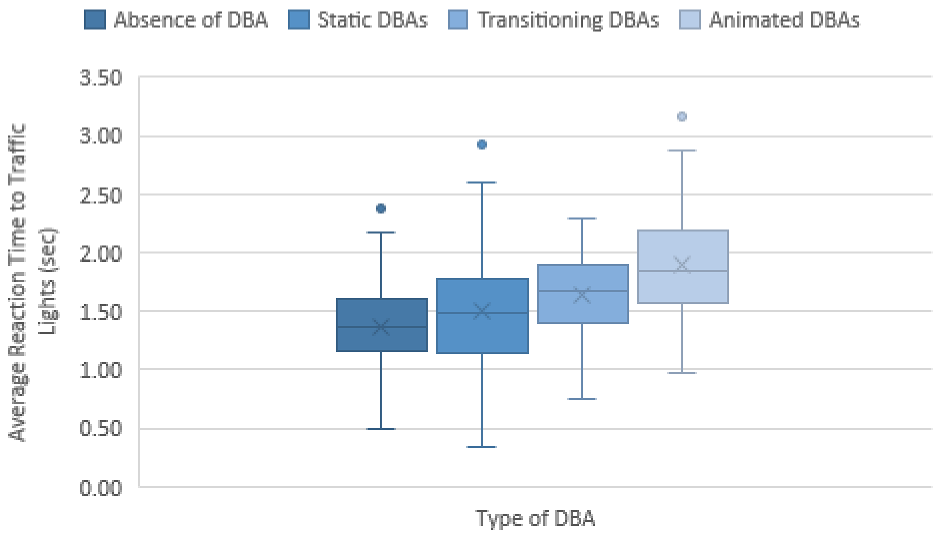


Figure 21. The average reaction time to traffic lights with the absence and presence of the three types of DBAs on the road

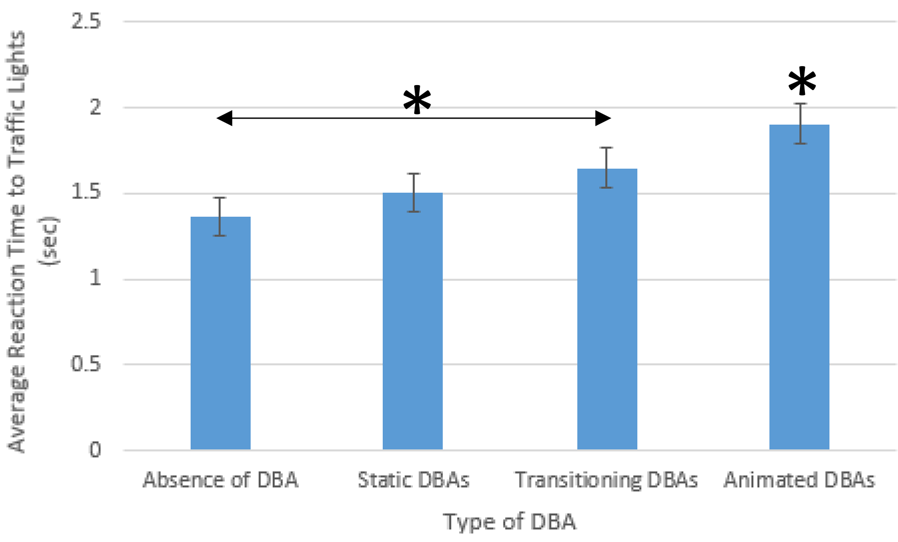


Figure 22. The statistically significant differences in the average reaction time to traffic lights data

5. Driving Performance Results Based on Gender

The females tended to reduce speed when they were exposed to static and transitioning DBAs compared to the absence of DBAs unlike males who increased their speed, relatively, compared to their speed with the absence of DBAs. As for other driving performance metrics, males and females exhibited similar behavior, increased deviation from the center of the lane and increased reaction time when exposed to static, transitioning, and animated DBAs.

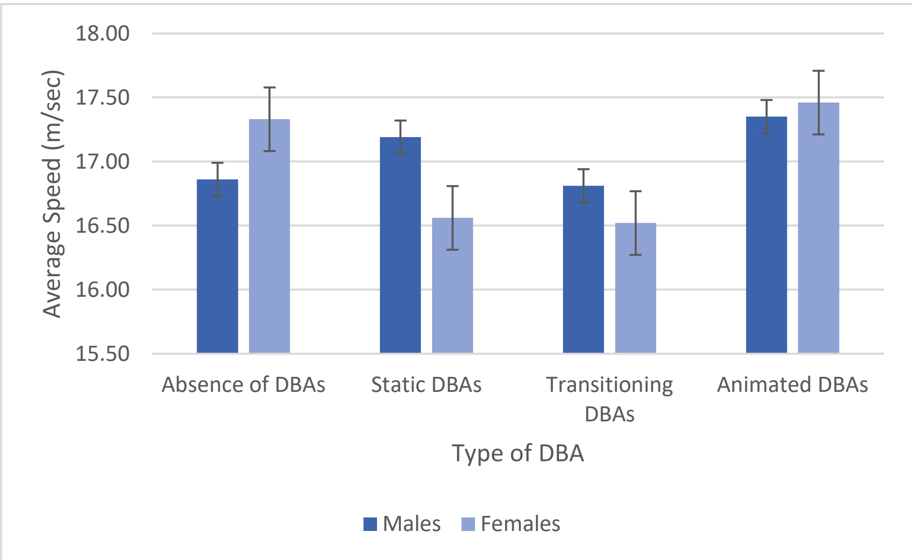


Figure 23. Average speed according to gender

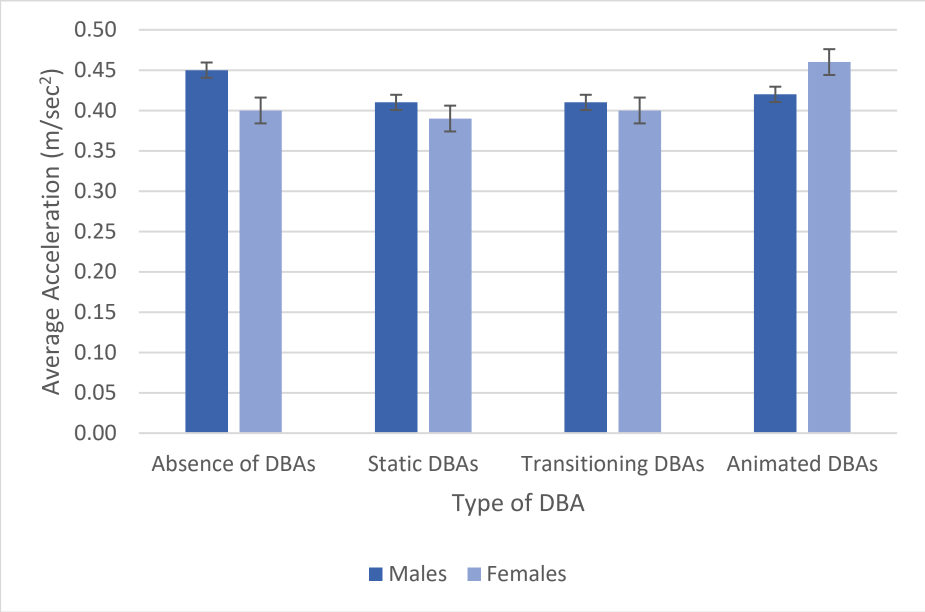


Figure 24. Average acceleration according to gender

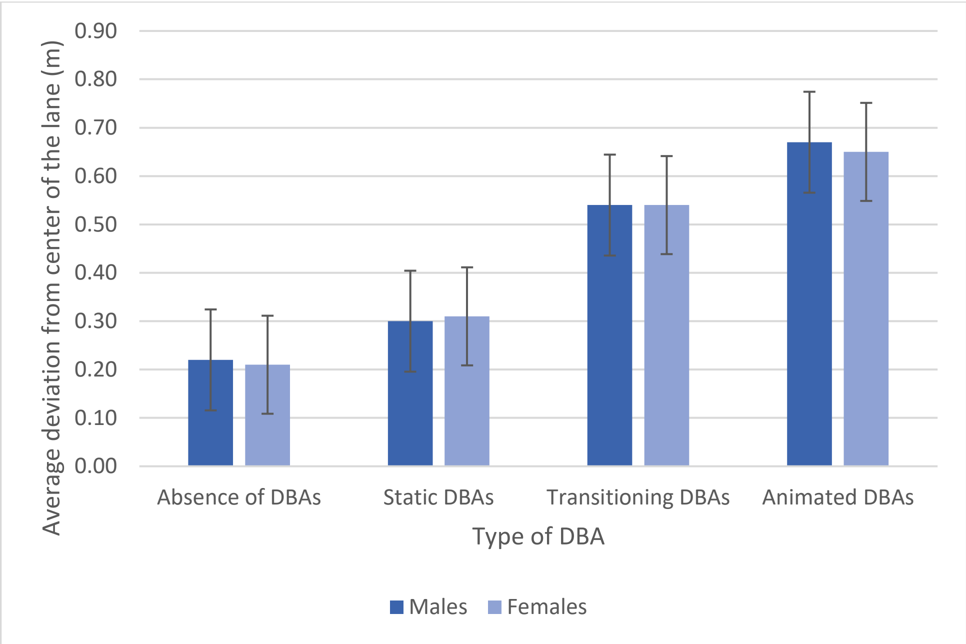


Figure 25. Average deviation from center of the lane according to gender

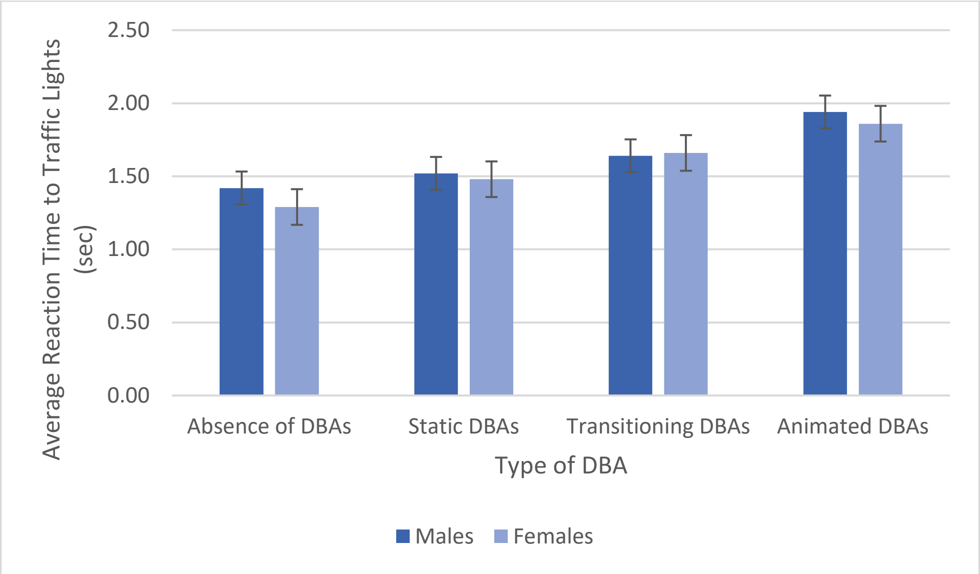


Figure 26. Average reaction time to traffic lights according to gender

6. Driving Performance Results Based on Age Groups

When exposed to static and animated DBAs, younger age groups tended to have higher speeds compared to older age groups. On the other hand, when exposed to transitioning DBAs, the age group between 18 and 22 had the lowest speed, following them were the group aged above 25 and the age group between 23 and 25. The youngest age group tended to deviate further from the center of the lane in the 4 cases and had the highest reaction time to traffic lights when exposed to animated DBAs at the intersection.

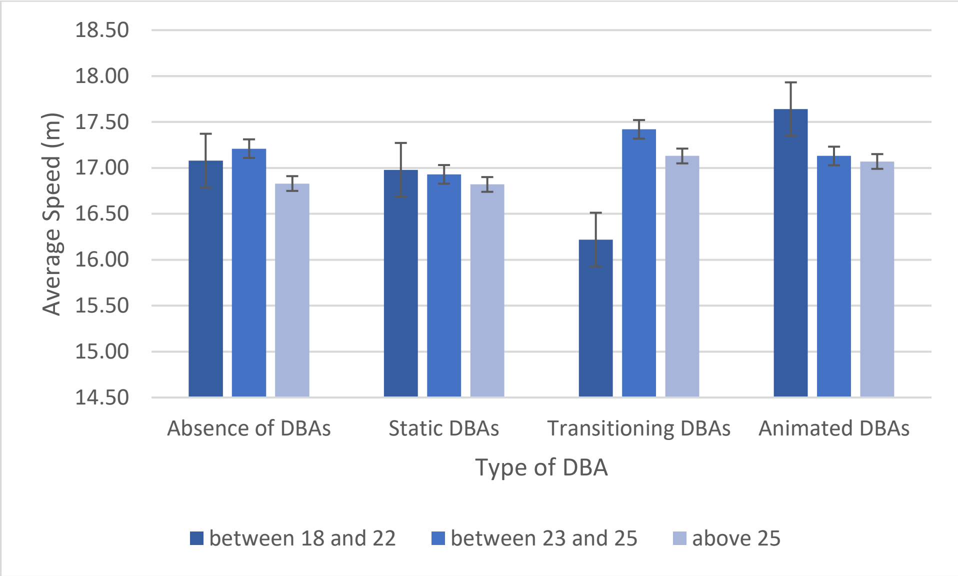


Figure 27. Average speed according to age group

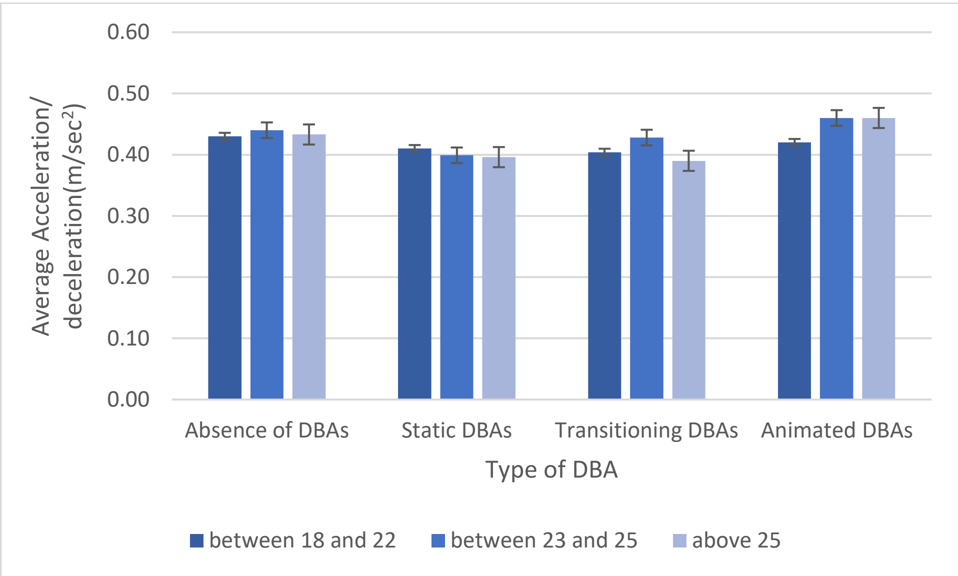


Figure 28. Average acceleration according to age group

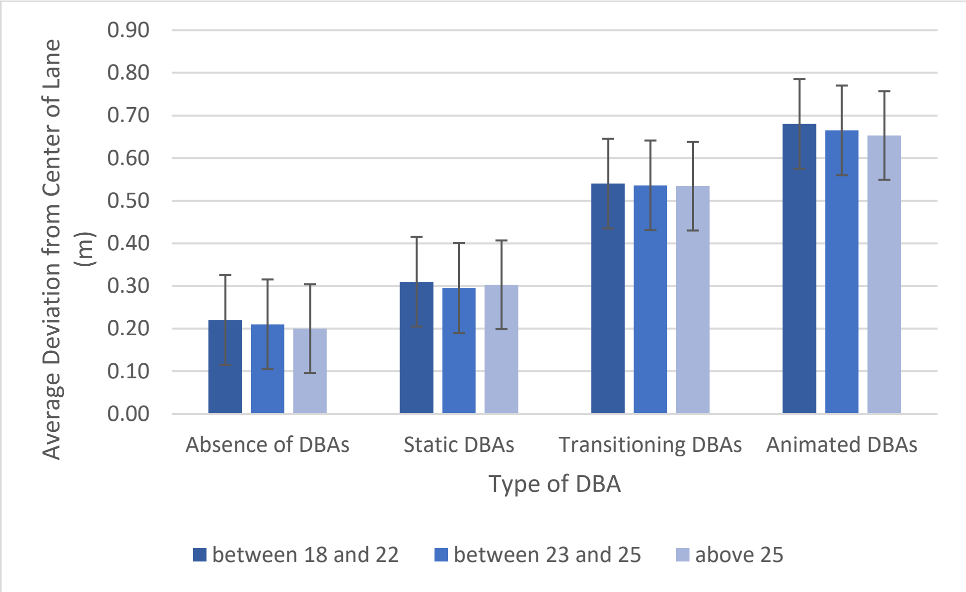


Figure 29. Average deviation from center of the lane according to age group

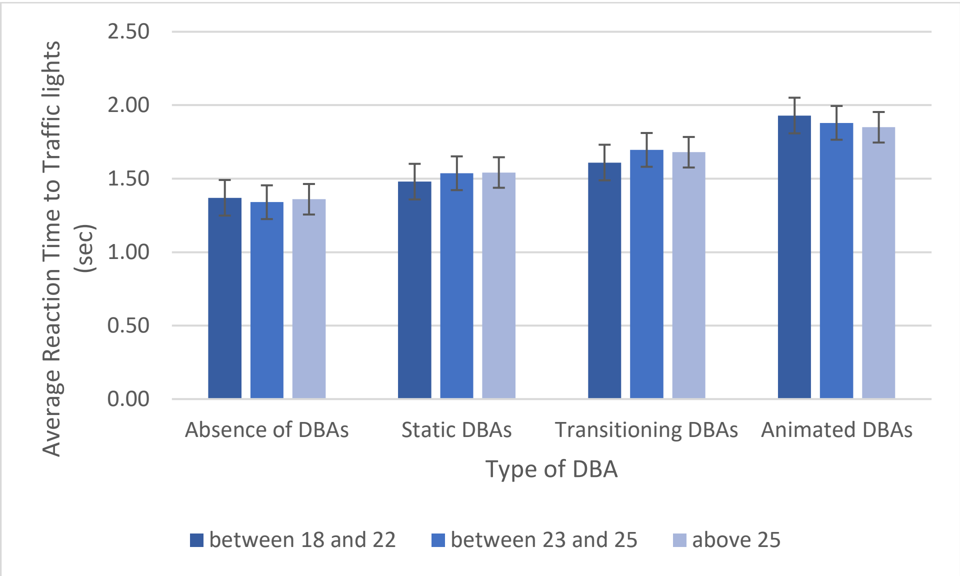


Figure 30. Average reaction time to traffic lights based on age group

7. Driving Performance Results Based on Years of Driving Experience

The group with driving experience of less than 5 years drove faster than the group with more than 5 years of driving experience except when exposed to transitioning DBAs where their speed decreased and was the lowest speed in the 4 cases examined. In terms of deviation from the center of the lane and the reaction time to traffic lights, the two age groups reacted generally in the same manner.

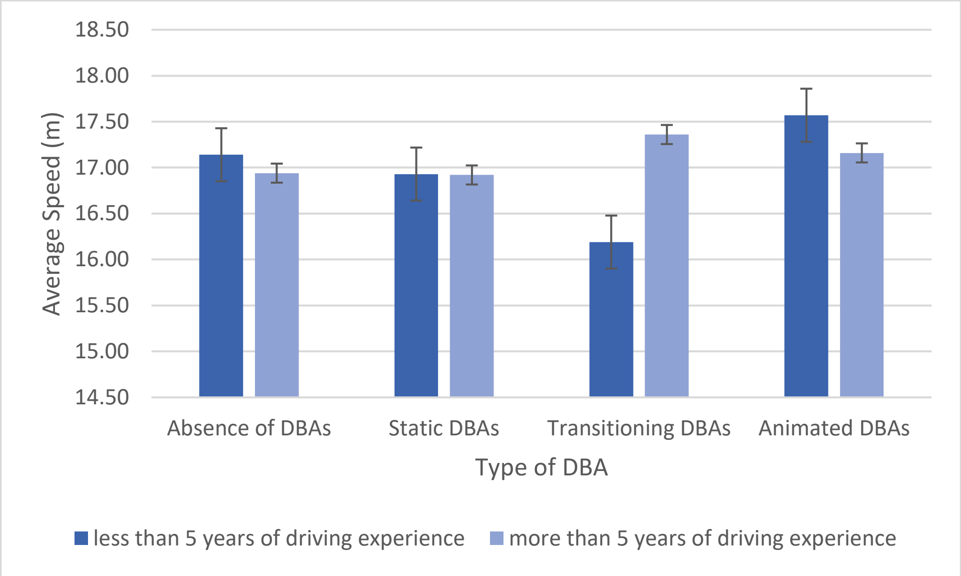


Figure 31. Average speed according to years of driving experience

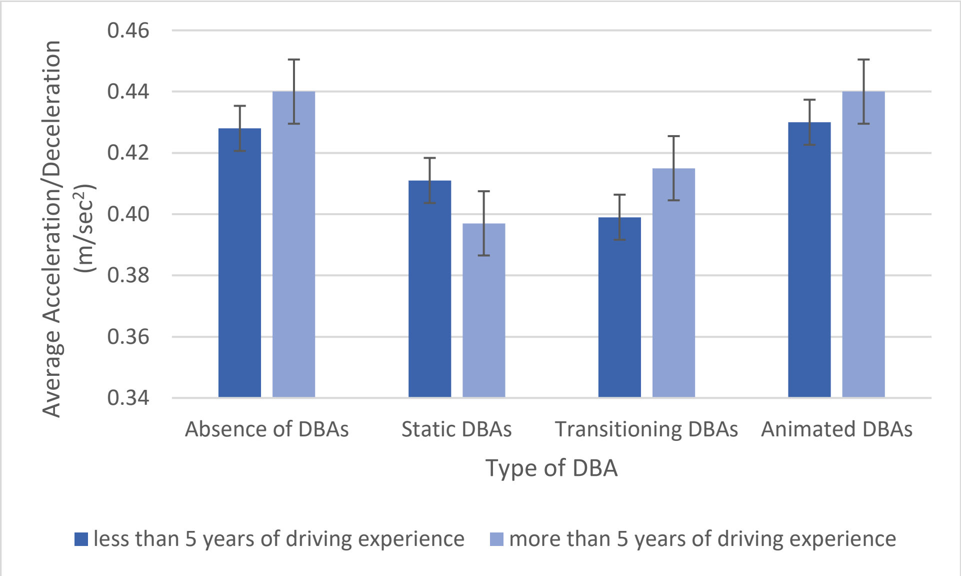


Figure 32. Average acceleration/deceleration according to years of experience

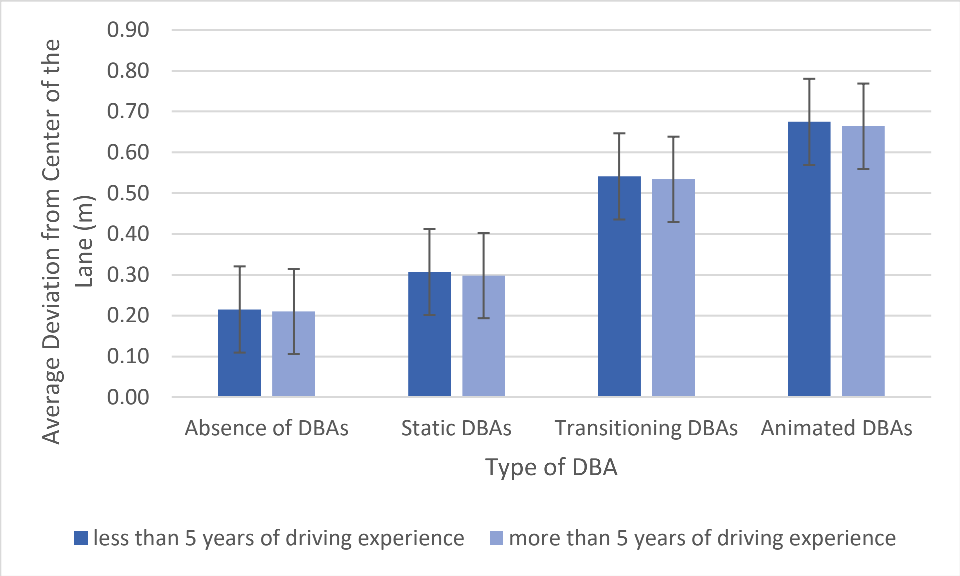


Figure 33. Average Deviation from center of the lane according to years of experience

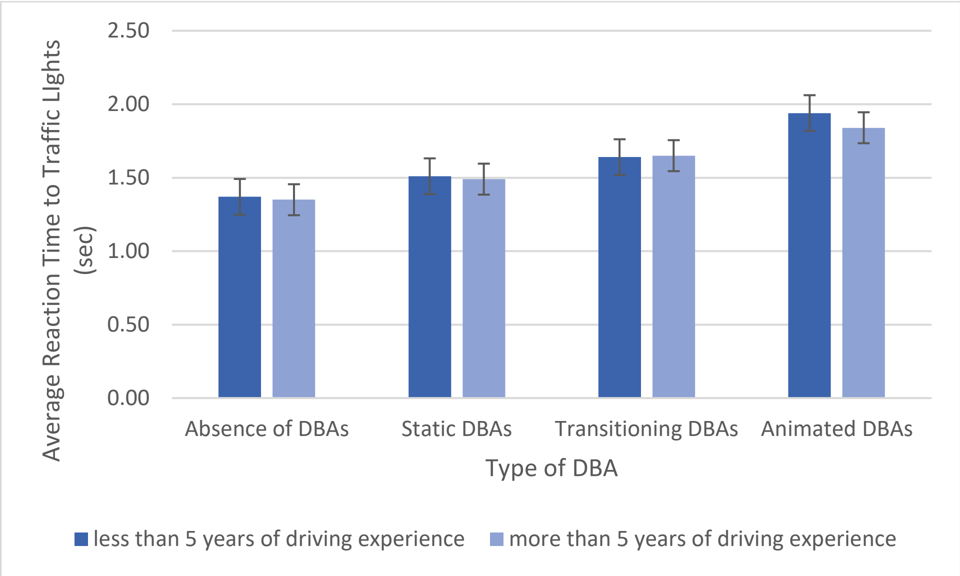


Figure 34. Average reaction time to traffic lights according to years of driving experience

B. Visual Behavior Statistical Analysis

1. Average Percentage of Fixations on the Road

An attempted one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the average percentage fixations on the road in the driving performance data of the 100 participants with four different cases: absence of DBA, presence of static, transitioning, or animated DBAs. There were relatively few outliers as assessed by boxplot. The data was not normally distributed at each time point as assessed by Shapiro-Wilk test ($p > .05$). Friedman non parametric test was run to determine if there were differences in the average percentage fixations of the four cases mentioned previously.

Pairwise comparisons were performed (SPSS Statistics, 2012) with a Bonferroni correction for multiple comparisons. The Average percentage of fixations on the road were statistically significantly different in animated DBAs and both the absence of DBAs and presence of static DBA ($p < .0005$). In addition to transitioning DBAs and both the absence of DBAs and presence of static DBA ($p < .0005$).

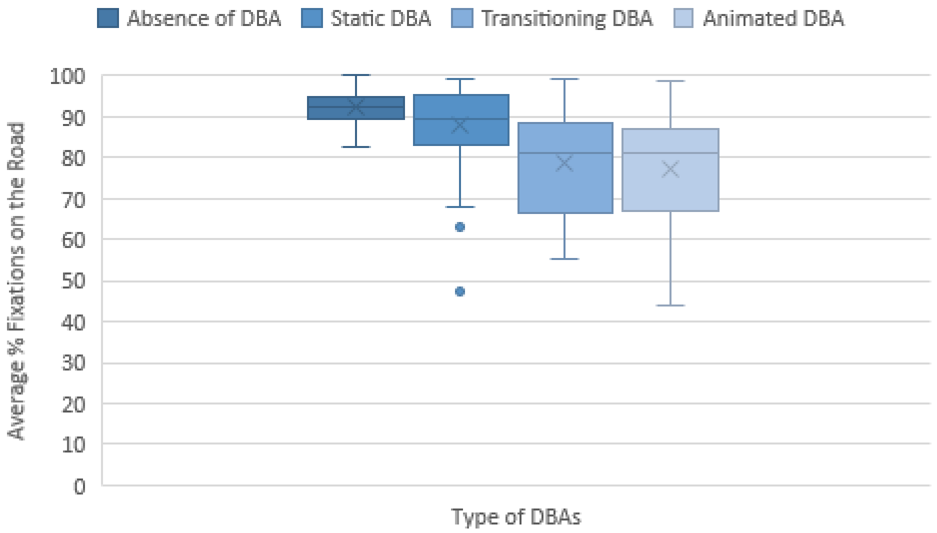


Figure 35. The average percentage fixations on the road with the absence and presence of the three types of DBAs on the road.

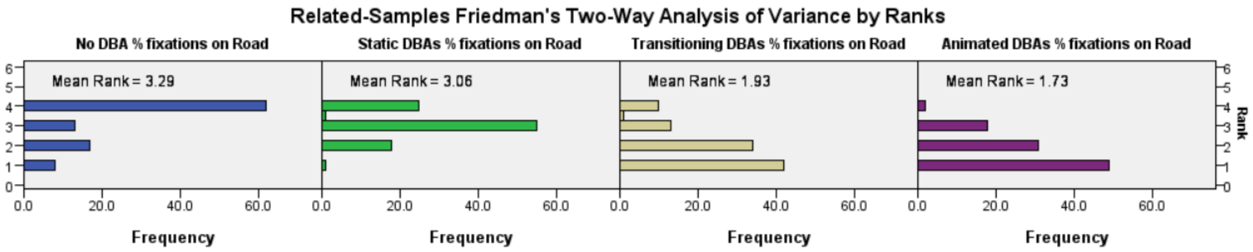
Hypothesis Test Summary

	Null Hypothesis	Test	Sig.	Decision
1	The distributions of No DBA % fixations on Road, Static DBAs % fixations on Road, Transitioning DBAs % fixations on Road and Animated DBAs % fixations on Road are the same.	Related-Samples Friedman's Two-Way Analysis of Variance by Ranks	.000	Reject the null hypothesis.

Asymptotic significances are displayed. The significance level is .05.

Median

No DBA % fixations on Road	Static DBAs % fixations on Road	Transitioning DBAs % fixations on Road	Animated DBAs % fixations on Road
92.4800	89.4250	81.2100	80.9700



Total N	100
Test Statistic	111.450
Degrees of Freedom	3
Asymptotic Sig. (2-sided test)	.000

Figure 36. Friedman's test applied on the average percentage fixations on the road data

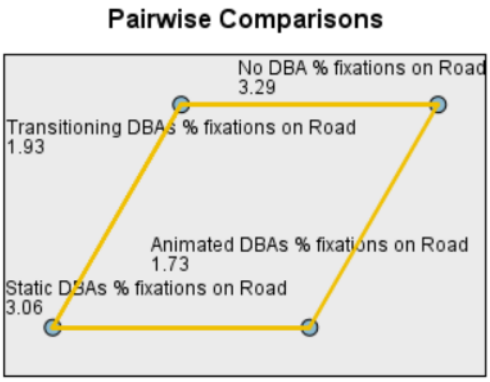


Figure 37. The pairwise comparisons in the average percentage fixations on the road data

2. Average Percentage of Fixations on the DBAs

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the average percentage of fixations on DBAs from the eye tracking data of the 100 participants while being exposed to the three different types of DBAs: static, transitioning, and animated. There were relatively few outliers and the data underwent a square root transformation to come closer to being normally distributed at each time point, as assessed by boxplot and Shapiro-Wilk test ($p > .05$), respectively. The assumption of sphericity had been violated, as assessed by

Mauchly's test of sphericity, $\chi 2$ (2) = 9.372, p =0.009. Therefore, a Greenhouse-Geisser correction was applied (ε = 0.916). The average percentage fixation on was statistically significantly different at the exposure of different types of DBAs, F (1.833, 181.451) =60.762, $p < .0005$, partial $\eta 2$ = 0.38.

The Average Percentage Fixation on DBAs increased from 3.18 ± 1.36 when exposed to static DBAs to 4.33± 1.57 when exposed to transitioning DBAs, to 4.53 ± 1.49 when exposed to animated DBAs, a statistically significant increase of 1.146 (95% CI, 0.831 to 1.461), $p < .0005$ and a statistically significant increase of 1.350 (95% CI, 1.069 to 1.630), $p < .0005$, respectively.

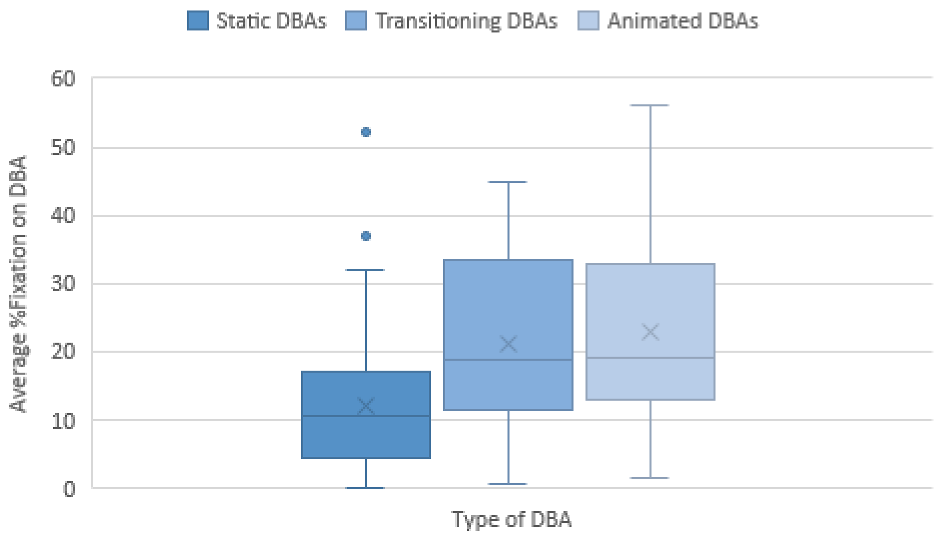


Figure 38. The average percentage fixations on DBAs with the presence of the three types of DBAs on the road

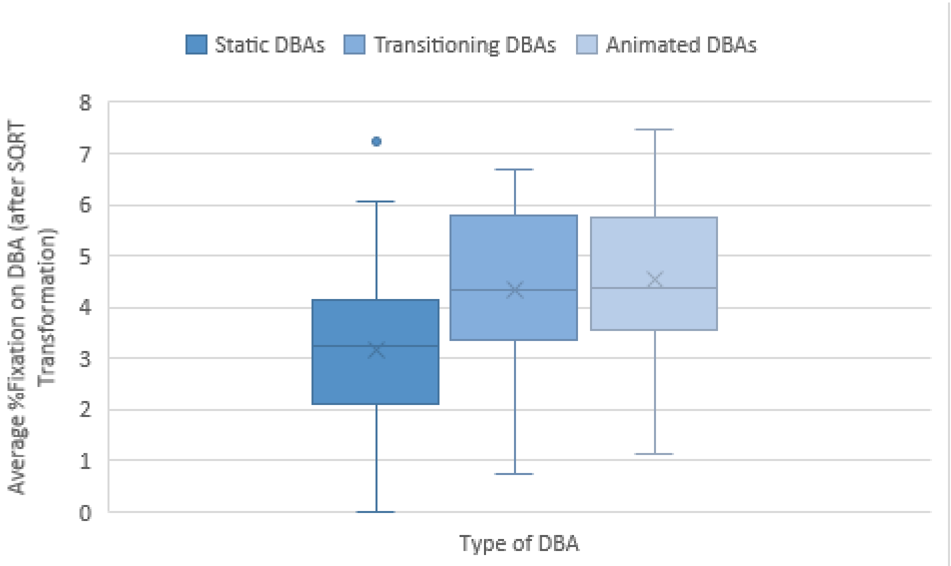


Figure 39. The average percentage fixations on DBAs with the presence of the three types of DBAs on the road after a square root transformation

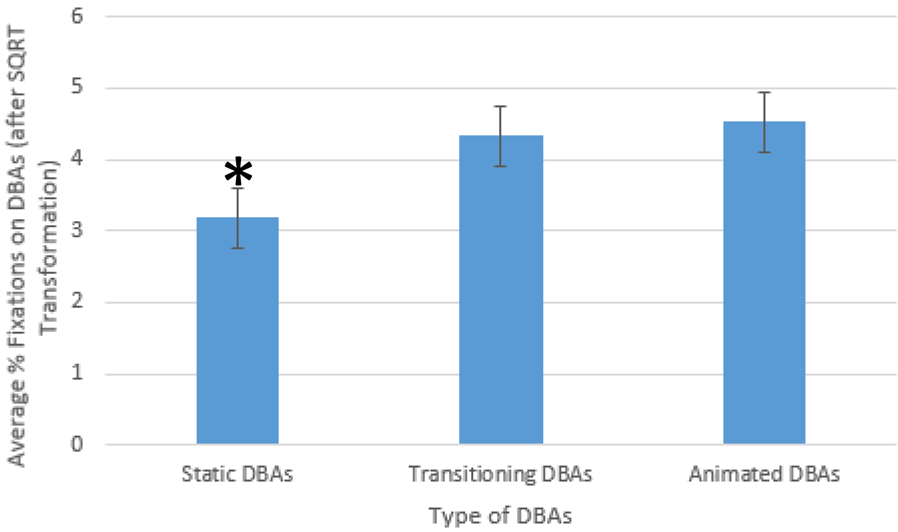


Figure 40. The statistically significant differences in the average percentage fixations on DBAs data after a square root transformation

3. Average Fixation Durations on the DBAs

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the average fixation durations on DBAs from the eye tracking data of the 100 participants while being exposed to the three different types of DBAs mentioned previously. There were relatively few outliers and the data is normally distributed at each time point, as assessed by boxplot and Shapiro-Wilk test ($p > .05$), respectively. The assumption of sphericity had been violated, as assessed by Mauchly's test of sphericity, $\chi 2$ (2) = 8.231, p =0.016. Therefore, a Greenhouse-Geisser correction was applied ($\varepsilon = 0.925$). Average fixation duration was statistically significantly different at the exposure of different types of DBAs, F (1.851, 183.239) =77.814, $p < .0005$, partial $\eta 2 = .44$.

The Average Fixation Duration on DBAs increased from 0.73 ± 0.47 seconds when exposed to static DBAs to 0.96± 0.53 seconds when exposed to transitioning DBAs, and to 1.57± 0.74 seconds when exposed to animated DBAs, a statistically significant increase of 0.228 (95% CI, 0.81 to 0.38) seconds, $p < .0005$ and 0.833 (95% CI, 0.667 to 0.998) seconds, $p < .0005$, respectively.

The Average Fixation Duration on DBAs increased from 0.96± 0.53 seconds when exposed to transitioning DBAs to 1.57± 0.74 seconds when exposed to animated DBAs, a statistically significant increase of 0.604 (95% CI, 0.79 to 0.42) seconds, $p < .0005$.

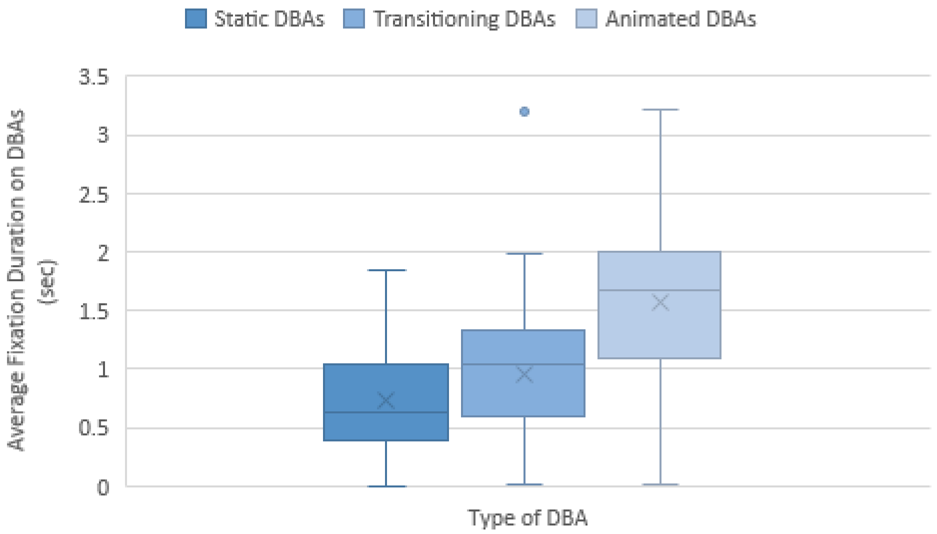


Figure 41. The average fixations durations on DBAs with the presence of the three types of DBAs on the road

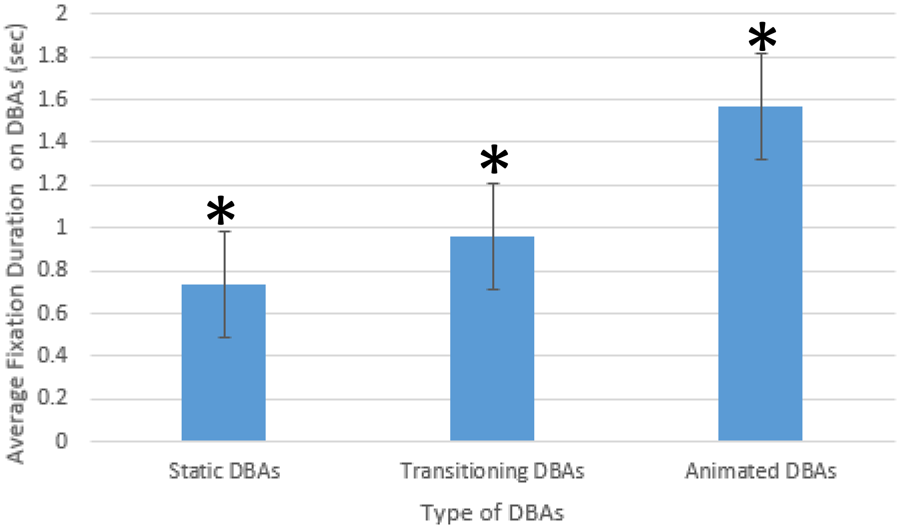


Figure 42.The statistically significant differences in the average fixations durations on DBAs data

4. Average Number of Gazes on the DBAs

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the number of gazes on DBAs from the eye tracking data of the 100 participants while being exposed to the three different types of DBAs mentioned previously. There were relatively few outliers and the data is normally distributed at each time point, as assessed by boxplot and Shapiro-Wilk test ($p > .05$), respectively. The assumption of sphericity had not been violated, as assessed by Mauchly's test of sphericity, $\chi 2$ (2) = 2.897, p =0.235. Number of Gazes on DBAs was statistically significantly different at the exposure of the different types of DBAs, F (2, 198) = 91.780, $p < .0005$, $\eta 2 = .481$.

The average number of gazes on DBAs increased from 1.24 ± 0.53 when exposed to static DBAs to 2.16± 0.89 when exposed to animated DBAs, and to 2.41± 0.79 when exposed to transitioning DBAs, a statistically significant increase of 0.915 (95% CI,1.130 to 0.669), p < .0005 and 1.168 (95% CI,1.376 to 0.960), $p < .0005$, respectively.

The average number of gazes on DBAs increased from 2.16± 0.89 when exposed to animated DBAs to 2.41± 0.79 when exposed to transitioning DBAs, a statistically significant increase of 0.253 (95% CI,0.492 to 0.015), p=0.033.

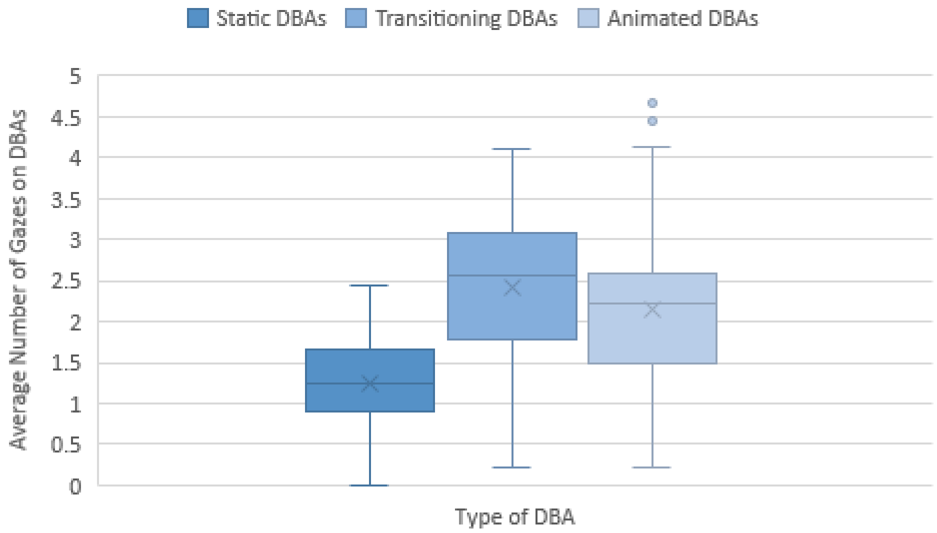


Figure 43. The average number of gazes on DBAs with the presence of the three types of DBAs on the road

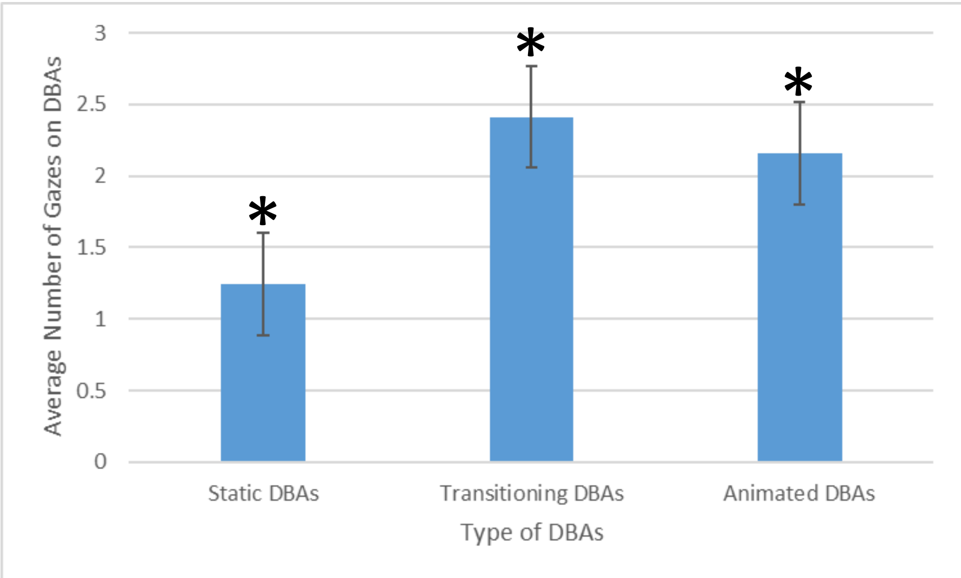


Figure 44. The statistically significant differences in the average number of gazes on DBAs data.

5. Eye Tracking Results Based on Gender

Male participants tended to have higher % fixations and fixation durations on transitioning DBAs than females who had higher % fixations and fixation durations on static and animated DBAs than males.

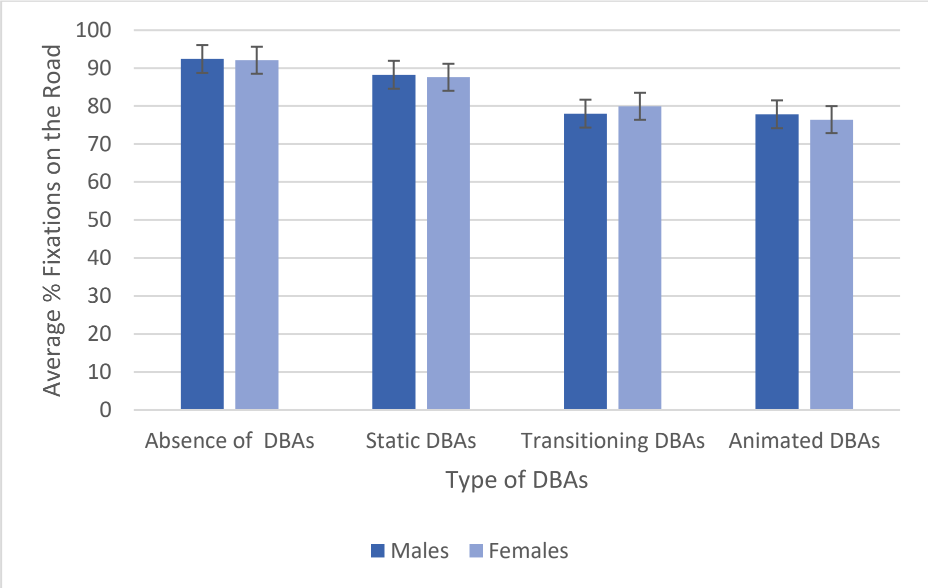


Figure 45. Average % fixations on the road according to gender

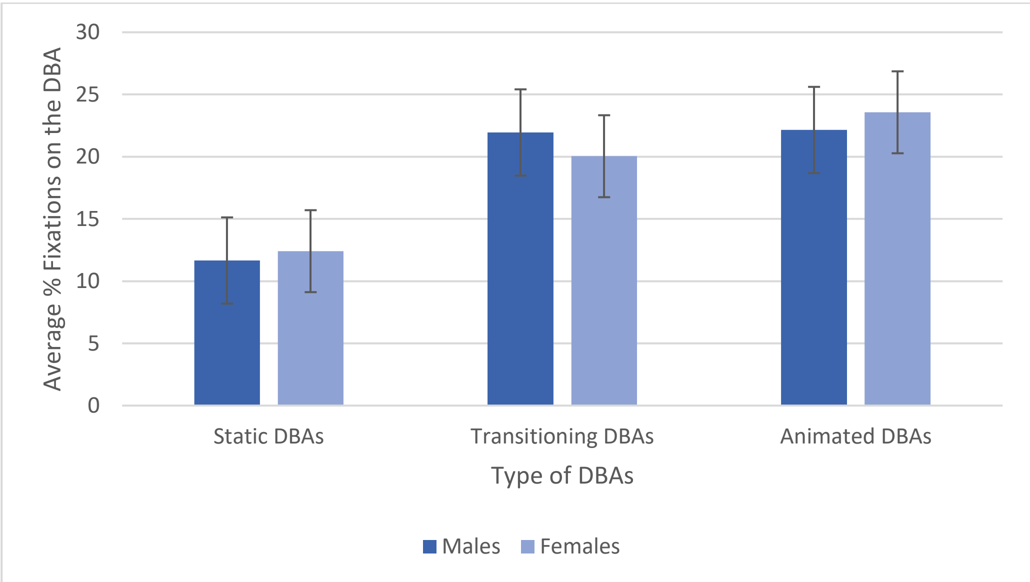


Figure 46. Average % fixations on the DBAs according to gender

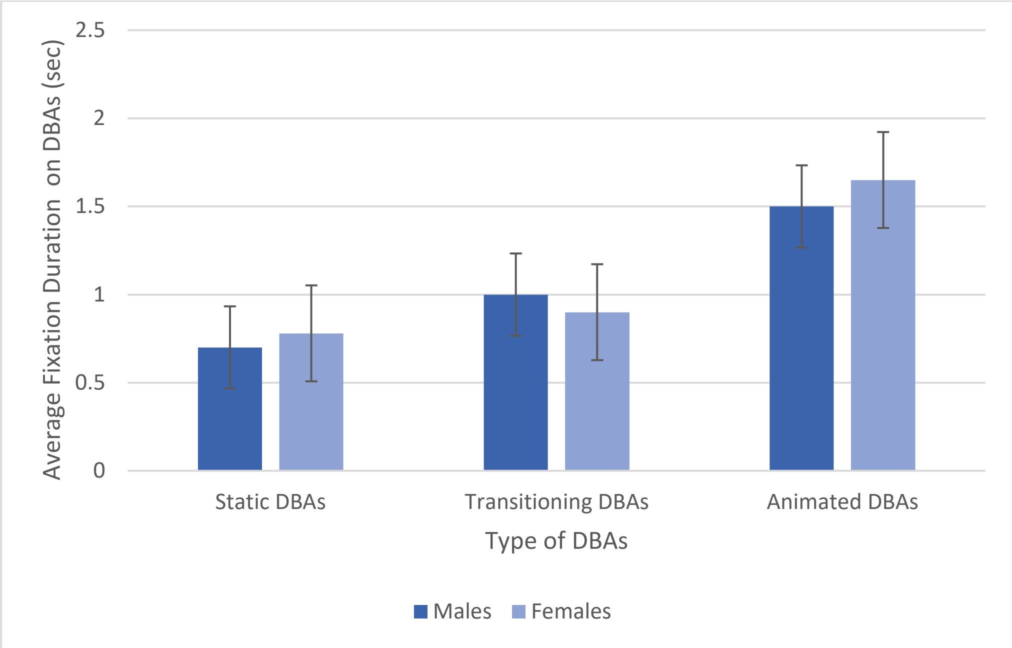


Figure 47. Average % fixation duration on DBA according to gender

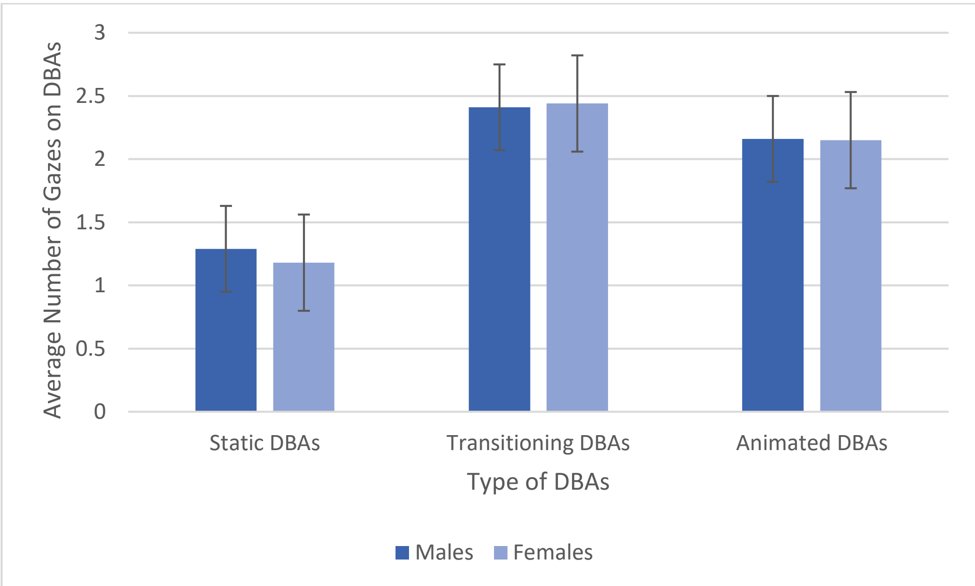


Figure 48. Average number of gazes on the DBA according to gender

6. Eye Tracking Results Based on Age Groups

Younger age groups tended to have higher % fixations, fixation durations, and number of gazes on DBAs than older age groups.

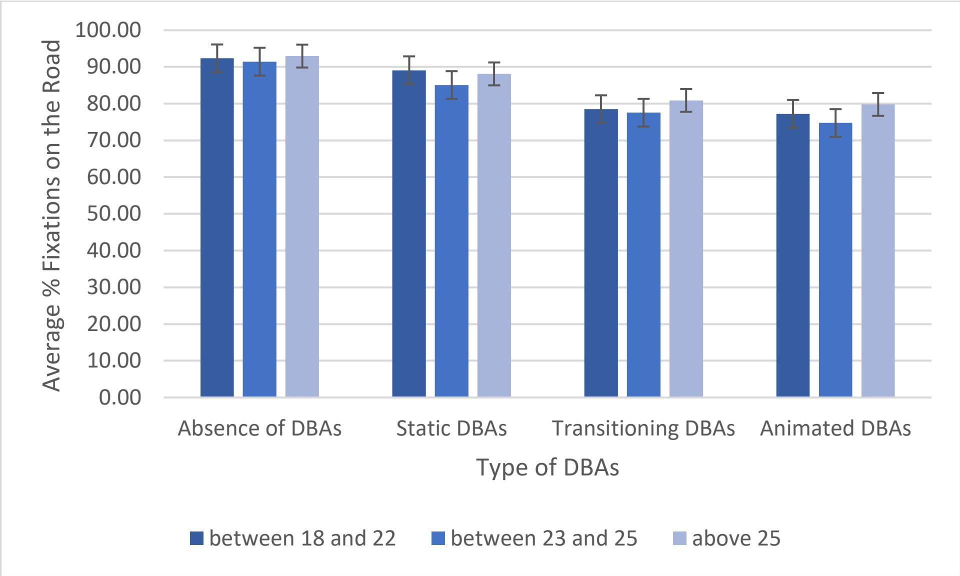


Figure 49. Average % fixations on the road according to age group

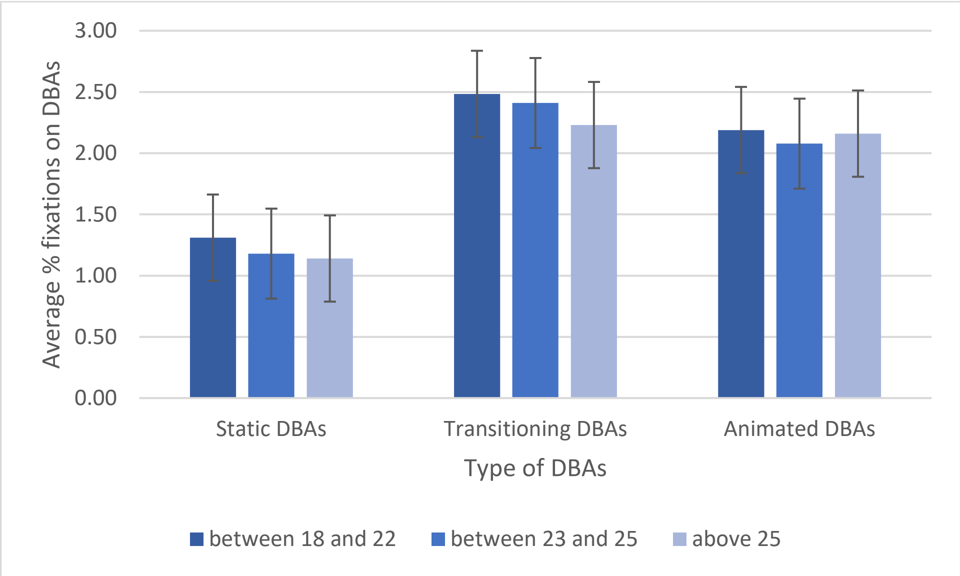


Figure 50. Average % fixations on DBAs according to age group

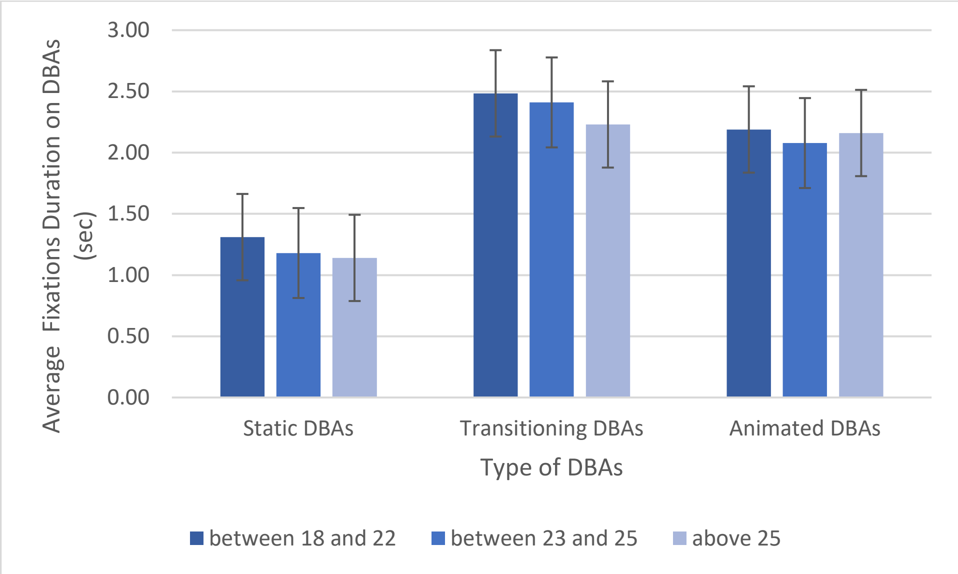


Figure 51. Average fixation Duration on DBAs according to age group

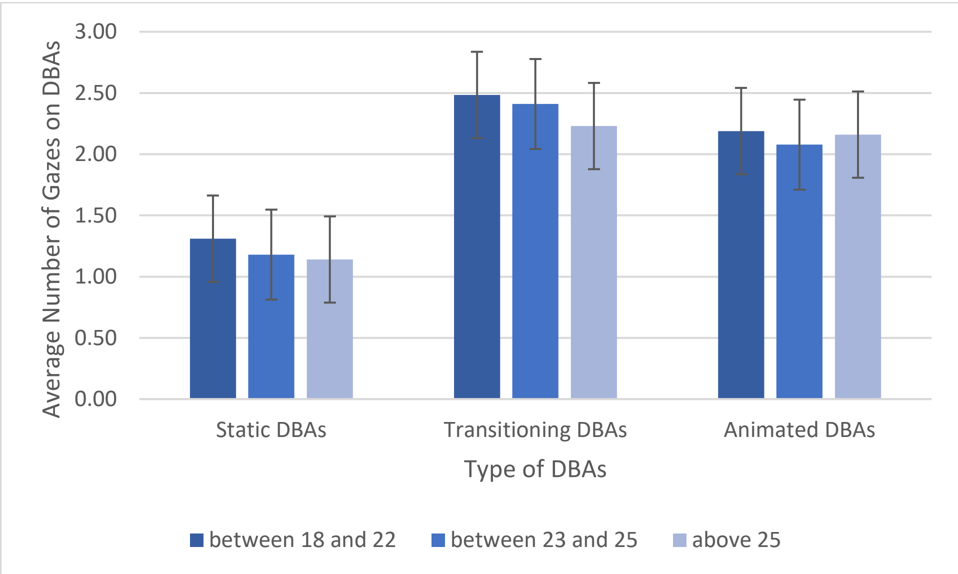


Figure 52. Average number of gazes on DBAs according to age groups

7. Eye Tracking Results Based on Years of Experience

Participants with more than 5 years of experience in driving had around 2-3% higher fixations on static and animated DBAs while those with less than 5 years of experience in driving had 5-7 % higher fixations on transitioning DBAs. However, the less experienced drivers showed higher fixation durations on all types of DBAs compared to experienced drivers.

The more experienced drivers exhibited higher number of gazes on transitioning and animated DBAs while the less experienced drivers exhibited more number of fixations on the static DBAs than the more experienced drivers.

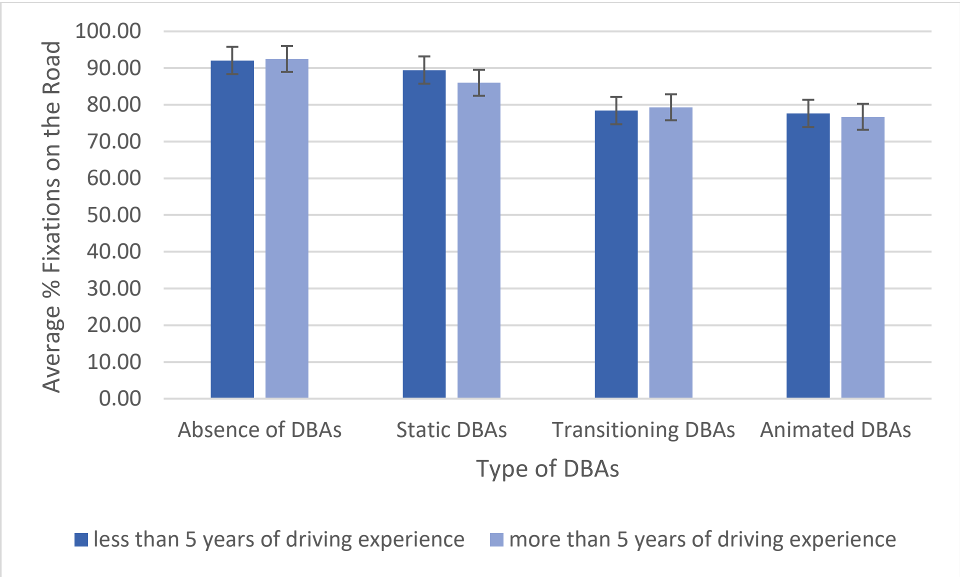


Figure 53. Average % fixations on the road according to years in driving experience

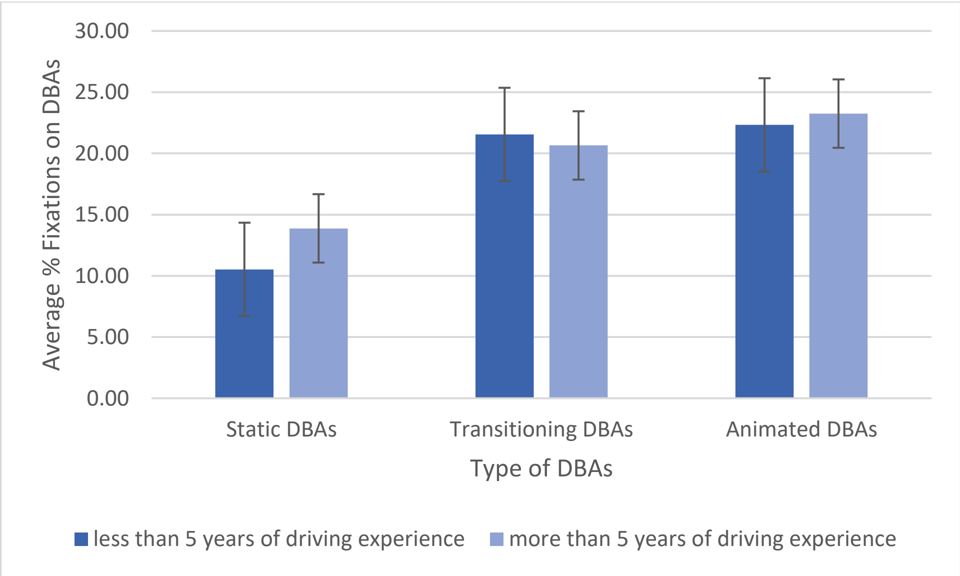


Figure 54. Average % Fixation on DBAs according to years in driving experience

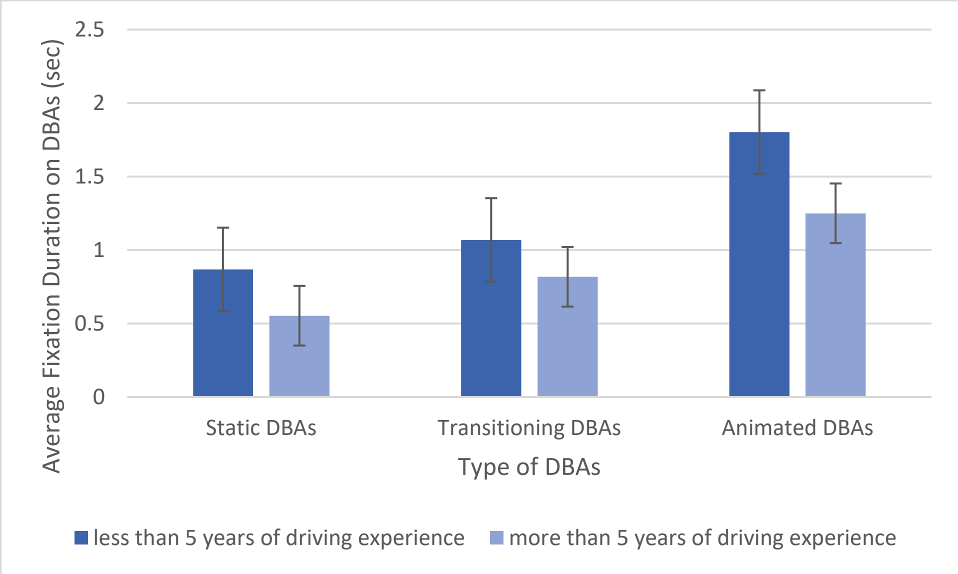


Figure 55. Average fixation duration on DBAs according to years in driving experience

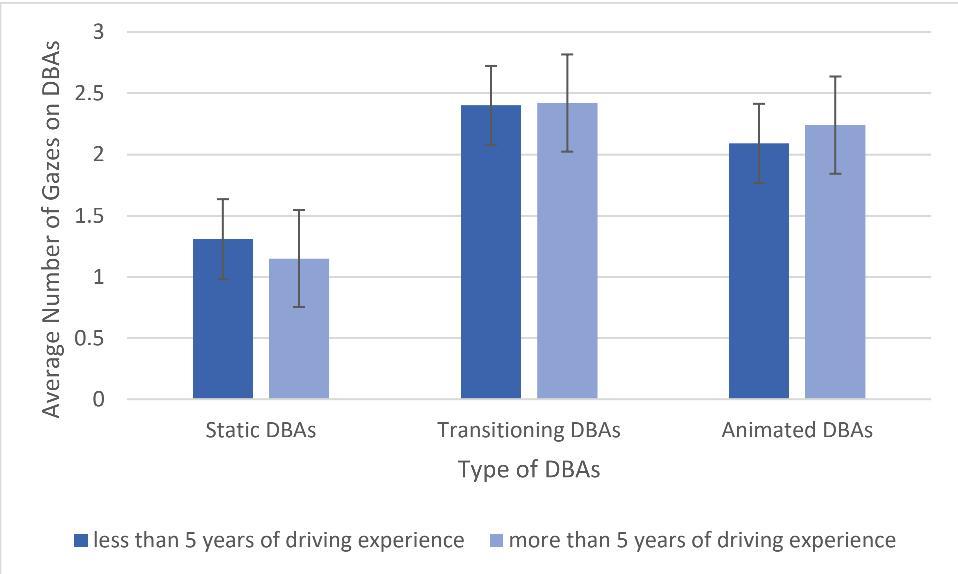


Figure 56. Average Number of Gazes on DBAs according to years in driving experience

C. EEG Statistical Analysis Results

1. Theta Band Power Statistical Analysis Results

An attempted one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the average theta band power in the extracted EEG data of the 100 participants with four different cases: absence of DBA, presence of static, transitioning, or animated DBAs. There were relatively few outliers as assessed by boxplot. The data was not normally distributed at each time point as assessed by Shapiro-Wilk test ($p > .05$). Friedman non parametric test was run to determine if there were differences in the average percentage fixations of the four cases mentioned previously.

Pairwise comparisons were performed (SPSS Statistics, 2012) with a Bonferroni correction for multiple comparisons. The average theta band power were statistically significantly different between the absence of DBAs and all the other cases (presence of any type of DBA) ($p < .0005$) and between the presence of animated DBAs and presence of static DBAs the absence of DBAs and presence of static DBAs ($p < .0005$).

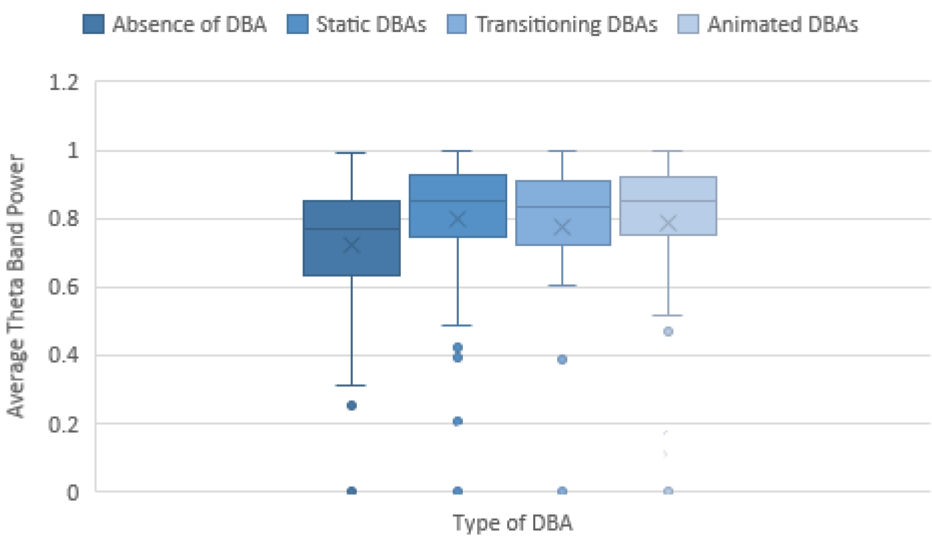
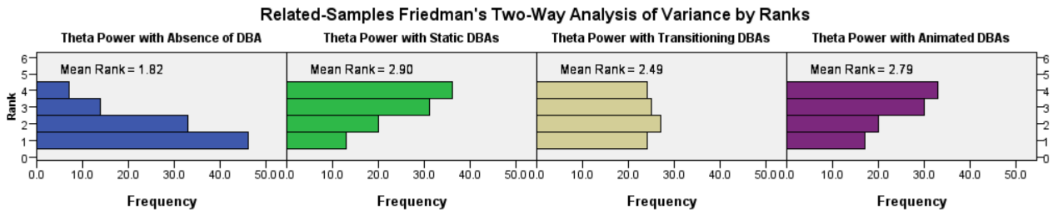


Figure 57. The average theta band power during the 4 different cases



Total N	100
Test Statistic	42.396
Degrees of Freedom	3
Asymptotic Sig. (2-sided test)	.000

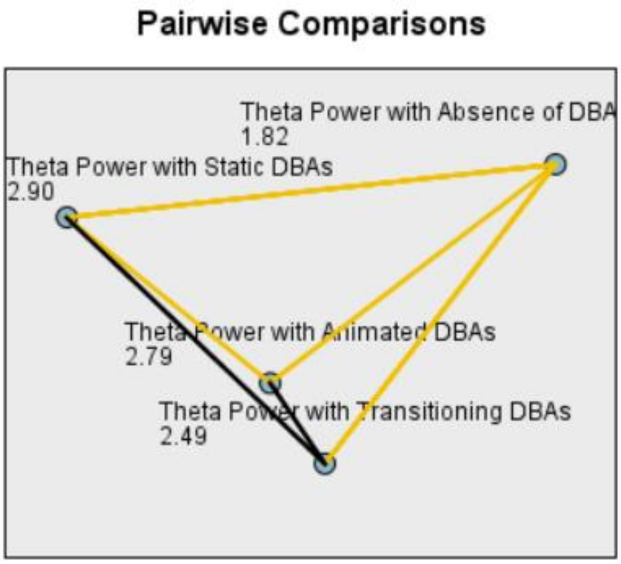


Figure 58. The pairwise comparisons of theta band power in the 4 cases

2. Alfa Band Power Statistical Analysis Results

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in average alfa band in the driving performance of the 100 participants in four different cases: absence of DBA, exposure to static DBAs, exposure to transitioning DBAs, and exposure to animated DBAs. There were relatively few outliers and the data was normally distributed at each time point, as assessed by boxplot and Shapiro-Wilk test ($p > .05$), respectively. Mauchly's test of sphericity indicated that the assumption of sphericity had not been violated, $\chi 2(2)$ =

7.908, *p* =0.161. The different exposure to DBAs did not lead to any statistically significant changes in Alfa power band, *F* (3, 297) = 1.581, *p* = .194, η2 = .016.

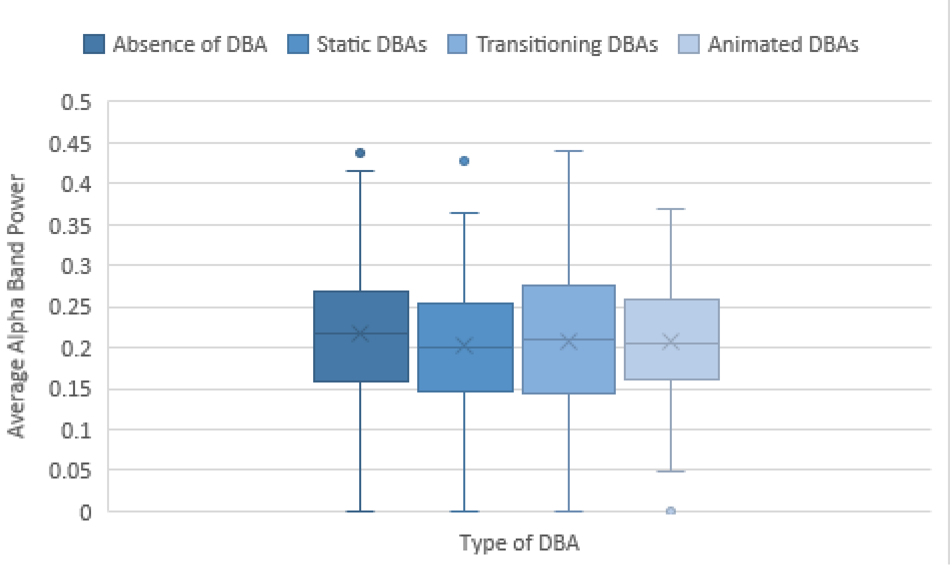


Figure 59. The average alpha band power during the 4 different cases

3. Low Beta Band Power Statistical Analysis Results

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the average low beta band power in the EEG data collected from the 100 participants with four different cases: absence of DBA, presence of static, transitioning, or animated DBAs. There were no outliers as assessed by boxplot. The data was normally distributed at each time point as assessed by Shapiro-Wilk test (*p* > .05).

The average Low-Beta power band when exposed to DBAs decreased from 0.1138 ± 0.05059 when there was absence of DBAs, to 0.1 ± 0.4833 when exposed to static DBAs, to 0.962 ± 0.05102 when exposed to transitioning DBAs, to 0.965 ± 0.05290 when exposed to animated with statistically significant differences of 0.014

(95% CI,0.23 to 0.004), p=0.001, 0.018 (95% CI,0.29 to 0.06), p=0.001,and 0.17 (95% CI,0.31 to 0.004), p=0.005, respectively.

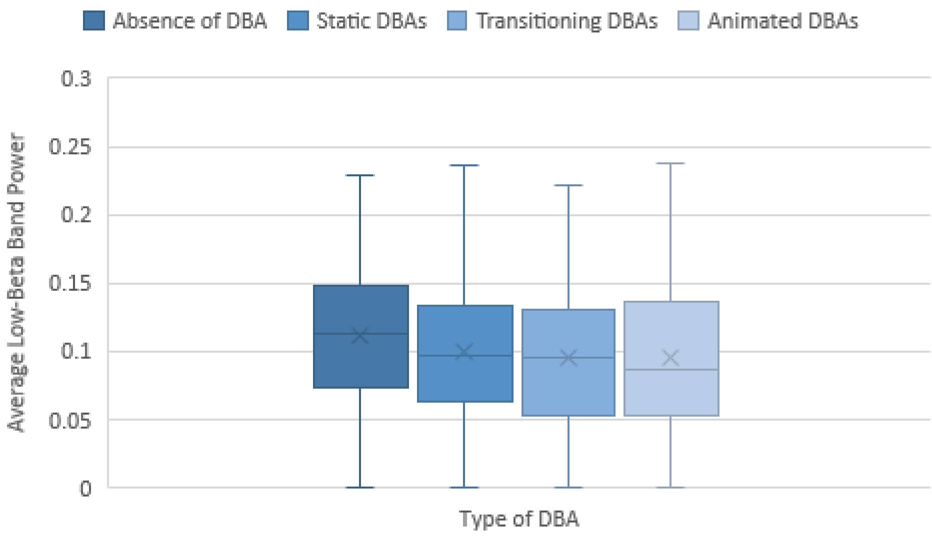


Figure 60. The average low beta band power during the 4 different cases

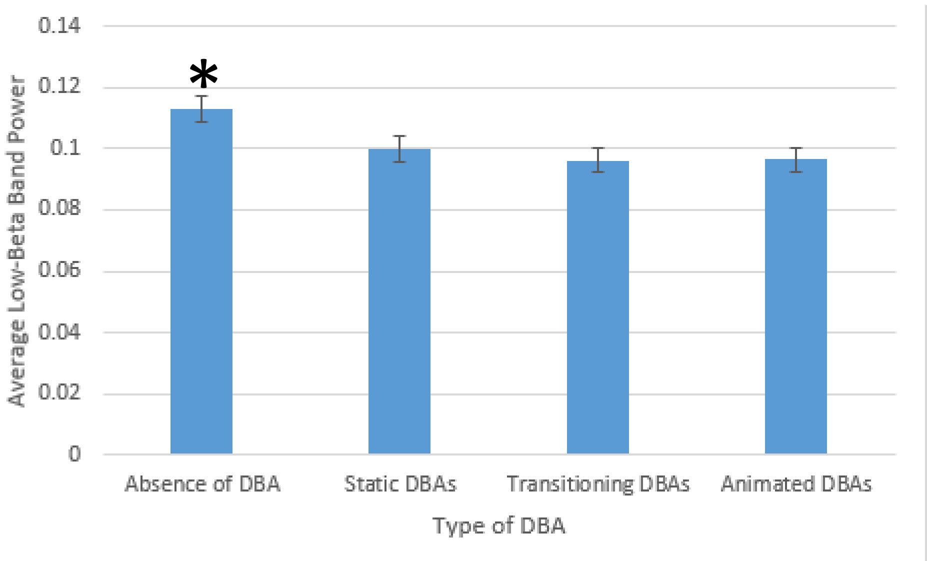


Figure 61. The statistically significant differences in the average low beta band power

4. High Beta Band Power Statistical Analysis Results

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the average high beta band power in the EEG data collected from the 100 participants with four different cases: absence of DBA, presence of static, transitioning, or animated DBAs. There were relatively few outliers as assessed by boxplot. The data was not normally distributed at each time point as assessed by Shapiro-Wilk test ($p > .05$). A square-root transformation was applied to adjust the data and make it close to normally distributed. Mauchly's test of sphericity indicated that the assumption of sphericity had not been violated, $\chi 2$ (2) = 5.603, p =0.347. The different exposure to DBAs did not lead to any statistically significant changes in High Beta power band, F (3, 297) = 0.665, p = .574, η^2 = .007.

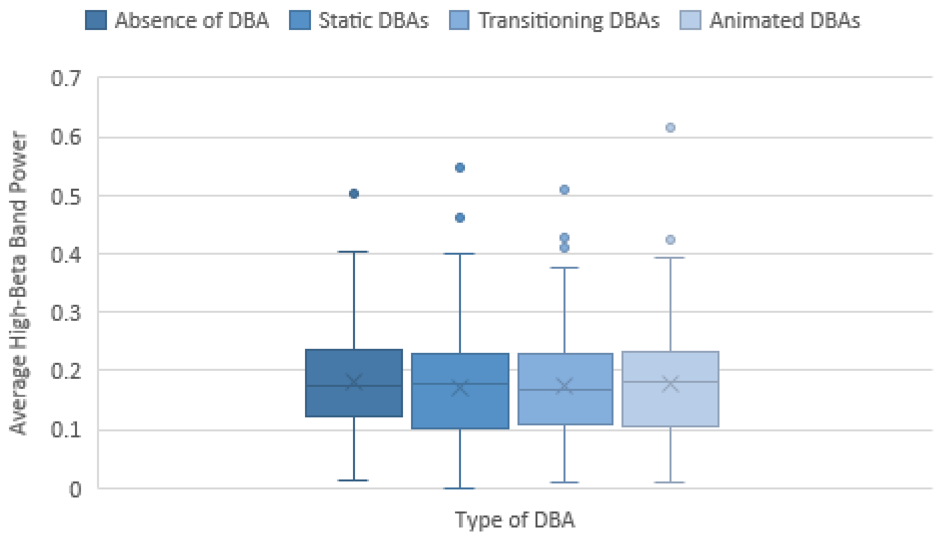


Figure 62. The average high beta band power during the 4 different cases

5. Gamma Band Power Statistical Analysis Results

A one-way repeated measures ANOVA was conducted to determine whether there was a statistically significant difference in the average gamma band power in the EEG data collected from the 100 participants with four different cases: absence of DBA, presence of static, transitioning, or animated DBAs. There were relatively few outliers as assessed by boxplot. The data was not normally distributed at each time point as assessed by Shapiro-Wilk test ($p > .05$). A square-root transformation was applied to adjust the data and make it close to normally distributed. Mauchly's test of sphericity indicated that the assumption of sphericity had not been violated, $\chi2$ (2) = 9.713, p =0.84. The different exposure to DBAs did not show any statistically significant changes in Gamma power band, F (3, 297) = 2.646, p = .049, $\eta2$ = .026.

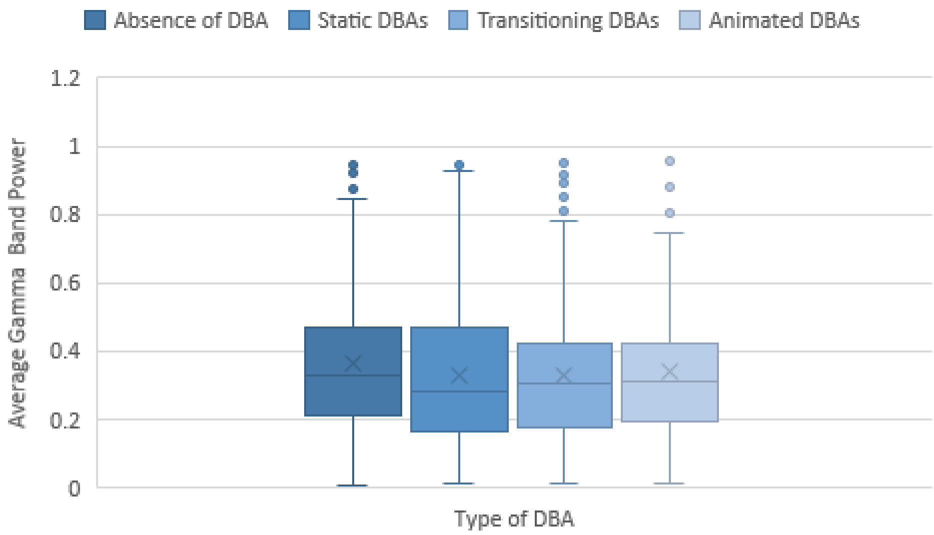


Figure 63. The average gamma band power during the 4 different cases

CHAPTER VII

RESULTS OF MACHINE LEARNING MODELS

A. Results of the machine learning models for detecting distraction caused by static DBAs

Table 7. Classification accuracies of static DBAs data using L1 labeling method

Static DBAs		**L1 without PCA**	**L1 with PCA 95%**	**L1 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	60%	67%	57%
Medium Tree	5	60%	67%	71%
Coarse Tree	5	64%	71%	75%
Linear SVM	5	75%	75%	75%
Quadratic SVM	5	59%	64%	75%
Cubic SVM	5	64%	61%	69%
Fine Gaussian SVM	5	75%	75%	**76%**
Medium Gaussian SVM	5	75%	75%	75%
Coarse Gaussian SVM	5	75%	75%	75%
Fine KNN	5	62%	62%	66%
Medium KNN	5	75%	75%	75%
Coarse KNN	5	75%	75%	75%
Cosine KNN	5	75%	75%	75%
Cubic KNN	5	74%	75%	75%
Weighted KNN	5	62%	66%	68%
Boosted Trees	5	54%	65%	67%
Bagged Trees	5	64%	67%	67%

Table 8. Classification accuracies of static DBAs data using L2 labeling method

Static DBAs		**L2 without PCA**	**L2 with PCA 95%**	**L2 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	61%	63%	65%
Medium Tree	5	61%	63%	65%
Coarse Tree	5	67%	68%	69%
Linear SVM	5	75%	75%	75%
Quadratic SVM	5	62%	68%	75%
Cubic SVM	5	57%	67%	76%

Fine Gaussian SVM	5	75%	76%	76%
Medium Gaussian SVM	5	75%	76%	76%
Coarse Gaussian SVM	5	75%	76%	76%
Fine KNN	5	59%	61%	65%
Medium KNN	5	72%	74%	75%
Coarse KNN	5	75%	75%	**77%**
Cosine KNN	5	74%	75%	**77%**
Cubic KNN	5	73%	73%	**77%**
Weighted KNN	5	62%	63%	69%
Boosted Trees	5	69%	73%	74%
Bagged Trees	5	70%	73%	76%

Table 9. Classification accuracies of static DBAs data using L3 labeling method

		L3 without PCA	**L3 with PCA 95%**	**L3 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	65%	68%	78%
Medium Tree	5	60%	65%	78%
Coarse Tree	5	68%	71%	78%
Linear SVM	5	73%	75%	79%
Quadratic SVM	5	62%	70%	79%
Cubic SVM	5	74%	62%	79%
Fine Gaussian SVM	5	75%	75%	79%
Medium Gaussian SVM	5	73%	75%	79%
Coarse Gaussian SVM	5	75%	75%	79%
Fine KNN	5	60%	63%	73%
Medium KNN	5	76%	82%	83%
Coarse KNN	5	75%	75%	79%
Cosine KNN	5	74%	76%	81%
Cubic KNN	5	74%	75%	81%
Weighted KNN	5	65%	74%	83%
Boosted Trees	5	60%	63%	75%
Bagged Trees	5	76%	77%	**85%**

Table 10. Classification accuracies of static DBAs data using L4 labeling method

Static DBAs		**L4 without PCA**	**L4 with PCA 95%**	**L4 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	**98%**	**98%**	**98%**
Medium Tree	5	**98%**	**98%**	**98%**
Coarse Tree	5	**98%**	**98%**	**98%**
Linear SVM	5	92%	94%	96%
Quadratic SVM	5	91%	93%	97%
Cubic SVM	5	89%	**98%**	**98%**
Fine Gaussian SVM	5	65%	96%	97%
Medium Gaussian SVM	5	70%	94%	95%
Coarse Gaussian SVM	5	69%	70%	82%
Fine KNN	5	84%	93%	97%
Medium KNN	5	88%	94%	97%
Coarse KNN	5	65%	65%	65%
Cosine KNN	5	85%	93%	93%
Cubic KNN	5	90%	94%	97%
Weighted KNN	5	88%	95%	**98%**
Boosted Trees	5	65%	65%	65%
Bagged Trees	5	97%	**98%**	**98%**

B. Results of the machine learning models for detecting distraction caused by transitioning DBAs

Table 11. Classification accuracies of transitioning DBAs data using L1 labeling method

Transitioning DBAs		**L1 without PCA**	**L1 with PCA 95%**	**L1 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	62%	62%	67%
Medium Tree	5	62%	62%	67%
Coarse Tree	5	68%	68%	73%
Linear SVM	5	75%	75%	75%
Quadratic SVM	5	71%	75%	75%
Cubic SVM	5	69%	74%	74%
Fine Gaussian SVM	5	72%	75%	75%
Medium Gaussian SVM	5	75%	75%	75%
Coarse Gaussian SVM	5	75%	75%	75%
Fine KNN	5	67%	67%	69%
Medium KNN	5	75%	75%	**76%**
Coarse KNN	5	75%	75%	75%

Cosine KNN	5	75%	75%	**76%**
Cubic KNN	5	75%	76%	**76%**
Weighted KNN	5	75%	70%	**76%**
Boosted Trees	5	59%	75%	**76%**
Bagged Trees	5	65%	68%	74%

Table 12. Classification accuracies of transitioning DBAs data using L2 labeling method

Transitioning DBAs		**L2 without PCA**	**L2 with PCA 95%**	**L2 with PCA 98%**
ML model	**CV**	**Accuracy**		
Fine Tree	5	61%	64%	64%
Medium Tree	5	61%	64%	64%
Coarse Tree	5	67%	68%	68%
Linear SVM	5	71%	**79%**	**79%**
Quadratic SVM	5	70%	**79%**	**79%**
Cubic SVM	5	69%	72%	72%
Fine Gaussian SVM	5	78%	**79%**	**79%**
Medium Gaussian SVM	5	**79%**	**79%**	**79%**
Coarse Gaussian SVM	5	**79%**	**79%**	**79%**
Fine KNN	5	61%	70%	72%
Medium KNN	5	**79%**	**79%**	**79%**
Coarse KNN	5	**79%**	**79%**	**79%**
Cosine KNN	5	**79%**	**79%**	**79%**
Cubic KNN	5	78%	**79%**	**79%**
Weighted KNN	5	67%	76%	77%
Boosted Trees	5	68%	78%	**79%**
Bagged Trees	5	67%	74%	76%

Table 13. Classification accuracies of transitioning DBAs data using L3 labeling method

Transitioning DBAs		**L3 without PCA**	**L3 with PCA 95%**	**L3 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	64%	75%	76%
Medium Tree	5	64%	76%	76%
Coarse Tree	5	67%	77%	77%
Linear SVM	5	75%	78%	**79%**
Quadratic SVM	5	73%	76%	77%
Cubic SVM	5	74%	75%	75%
Fine Gaussian SVM	5	75%	75%	75%

Medium Gaussian SVM	5	75%	77%	78%
Coarse Gaussian SVM	5	75%	75%	75%
Fine KNN	5	63%	72%	72%
Medium KNN	5	76%	76%	76%
Coarse KNN	5	75%	75%	75%
Cosine KNN	5	75%	78%	78%
Cubic KNN	5	76%	77%	77%
Weighted KNN	5	65%	78%	78%
Boosted Trees	5	75%	65%	65%
Bagged Trees	5	68%	70%	81%

Table 14. Classification accuracies of transitioning DBAs data using L4 labeling method

Transitioning DBAs		**L4 without PCA**	**L4 with PCA 95%**	**L4 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	98%	**99%**	**99%**
Medium Tree	5	98%	**99%**	**99%**
Coarse Tree	5	98%	**99%**	**99%**
Linear SVM	5	94%	96%	96%
Quadratic SVM	5	93%	98%	98%
Cubic SVM	5	93%	**99%**	**99%**
Fine Gaussian SVM	5	55%	96%	96%
Medium Gaussian SVM	5	91%	96%	96%
Coarse Gaussian SVM	5	93%	94%	94%
Fine KNN	5	82%	97%	97%
Medium KNN	5	89%	**99%**	**99%**
Coarse KNN	5	55%	55%	55%
Cosine KNN	5	91%	97%	97%
Cubic KNN	5	86%	98%	98%
Weighted KNN	5	88%	98%	98%
Boosted Trees	5	55%	55%	55%
Bagged Trees	5	98%	**99%**	**99%**

C. Results of the machine learning models for detecting distraction caused by animated DBAs

Table 15. Classification of animated DBAs data using L1 labeling method

Animated DBAs		**L1 without PCA**	**L1 with PCA 95%**	**L1 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	58%	61%	69%
Medium Tree	5	58%	61%	69%
Coarse Tree	5	64%	65%	71%
Linear SVM	5	75%	76%	**77%**
Quadratic SVM	5	56%	76%	**77%**
Cubic SVM	5	57%	76%	**77%**
Fine Gaussian SVM	5	75%	76%	**77%**
Medium Gaussian SVM	5	75%	76%	**77%**
Coarse Gaussian SVM	5	75%	76%	75%
Fine KNN	5	53%	56%	59%
Medium KNN	5	75%	76%	**77%**
Coarse KNN	5	75%	76%	**77%**
Cosine KNN	5	76%	76%	**77%**
Cubic KNN	5	76%	76%	**77%**
Weighted KNN	5	64%	73%	74%
Boosted Trees	5	60%	62%	65%
Bagged Trees	5	57%	64%	69%

Table 16. Classification of animated DBAs data using L2 labeling method

Animated DBAs		**L2 without PCA**	**L2 with PCA 95%**	**L2 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	55%	62%	66%
Medium Tree	5	55%	62%	66%
Coarse Tree	5	61%	70%	71%
Linear SVM	5	75%	75%	**76%**
Quadratic SVM	5	64%	75%	**76%**
Cubic SVM	5	58%	65%	69%
Fine Gaussian SVM	5	75%	75%	**76%**
Medium Gaussian SVM	5	75%	75%	**76%**
Coarse Gaussian SVM	5	75%	75%	**76%**
Fine KNN	5	62%	62%	62%
Medium KNN	5	74%	75%	75%
Coarse KNN	5	75%	75%	**76%**
Cosine KNN	5	75%	75%	**76%**
Cubic KNN	5	75%	75%	75%
Weighted KNN	5	75%	75%	75%

Boosted Trees	5	68%	75%	75%
Bagged Trees	5	63%	65%	71%

Table 17. Classification of animated DBAs data using L3 labeling method

Animated DBAs		**L3 without PCA**	**L3 with PCA 95%**	**L3 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	62%	68%	81%
Medium Tree	5	62%	68%	81%
Coarse Tree	5	68%	77%	84%
Linear SVM	5	75%	75%	83%
Quadratic SVM	5	75%	75%	78%
Cubic SVM	5	50%	71%	78%
Fine Gaussian SVM	5	75%	75%	75%
Medium Gaussian SVM	5	75%	75%	87%
Coarse Gaussian SVM	5	75%	75%	75%
Fine KNN	5	64%	66%	76%
Medium KNN	5	70%	73%	80%
Coarse KNN	5	75%	75%	75%
Cosine KNN	5	69%	75%	81%
Cubic KNN	5	70%	73%	77%
Weighted KNN	5	66%	70%	81%
Boosted Trees	5	65%	66%	75%
Bagged Trees	5	63%	66%	**87%**

Table 18. Classification of animated DBAs data using L4 labeling method

Animated DBAs		**L4 without PCA**	**L4 with PCA 95%**	**L4 with PCA 98%**
ML model	**CV**		**Accuracy**	
Fine Tree	5	**100%**	**100%**	**100%**
Medium Tree	5	**100%**	**100%**	**100%**
Coarse Tree	5	**100%**	**100%**	**100%**
Linear SVM	5	99%	99%	99%
Quadratic SVM	5	95%	98%	99%
Cubic SVM	5	92%	99%	99%
Fine Gaussian SVM	5	88%	99%	**100%**
Medium Gaussian SVM	5	96%	99%	99%
Coarse Gaussian SVM	5	81%	90%	93%
Fine KNN	5	88%	**100%**	**100%**
Medium KNN	5	87%	**100%**	**100%**
Coarse KNN	5	56%	56%	56%
Cosine KNN	5	89%	**100%**	**100%**

Cubic KNN	5	85%	**100%**	**100%**
Weighted KNN	5	86%	**100%**	**100%**
Boosted Trees	5	56%	56%	56%
Bagged Trees	5	**100%**	**100%**	**100%**

D. Unsupervised Clustering Model Results

1. Results of Clustering Static DBAs data

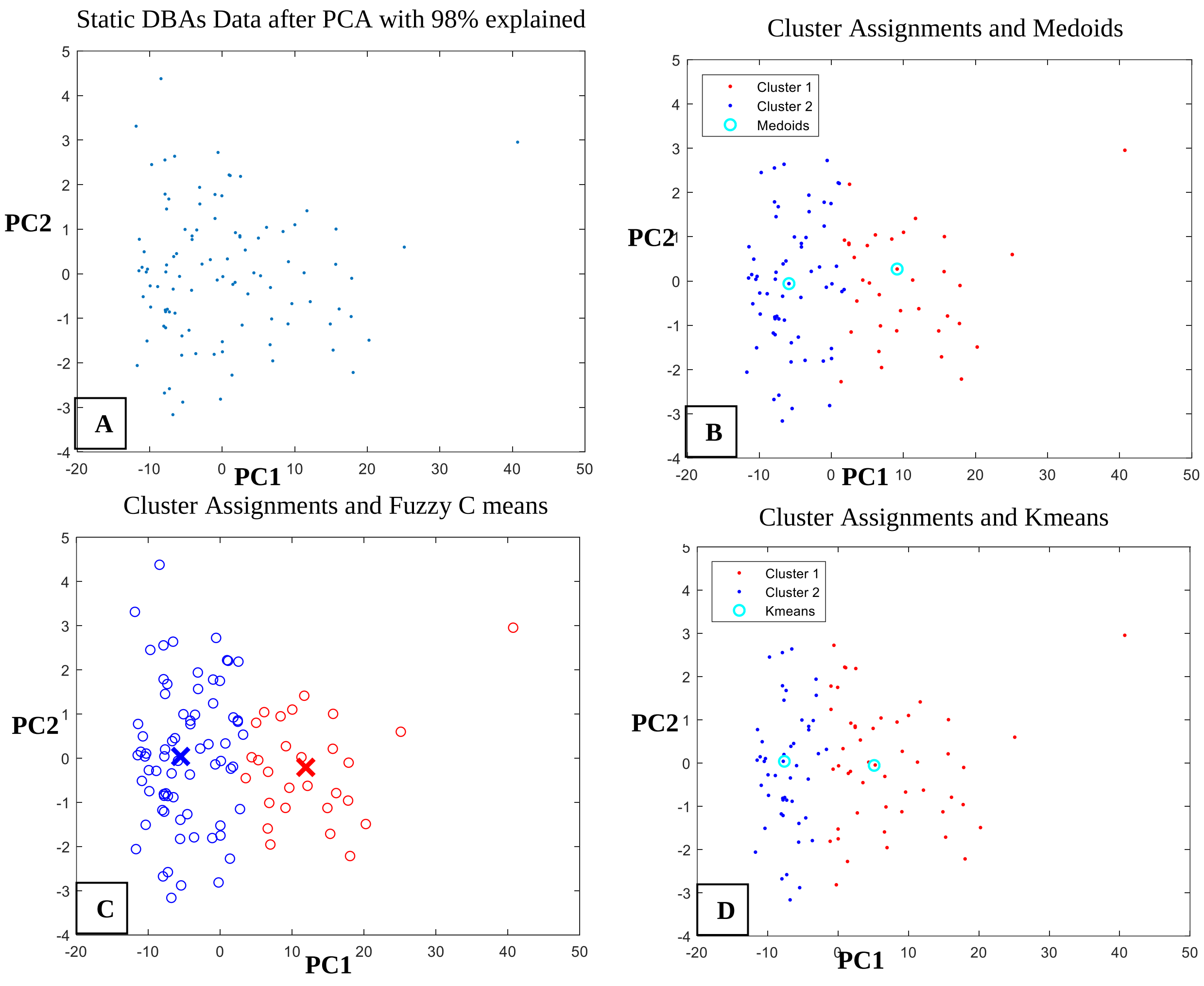


Figure 64. Clustering of static DBAs data “A” using Kmedoids “B”, Fuzzy C means “C”, and Kmeans “D”

2. Results of Clustering Transitioning DBAs data

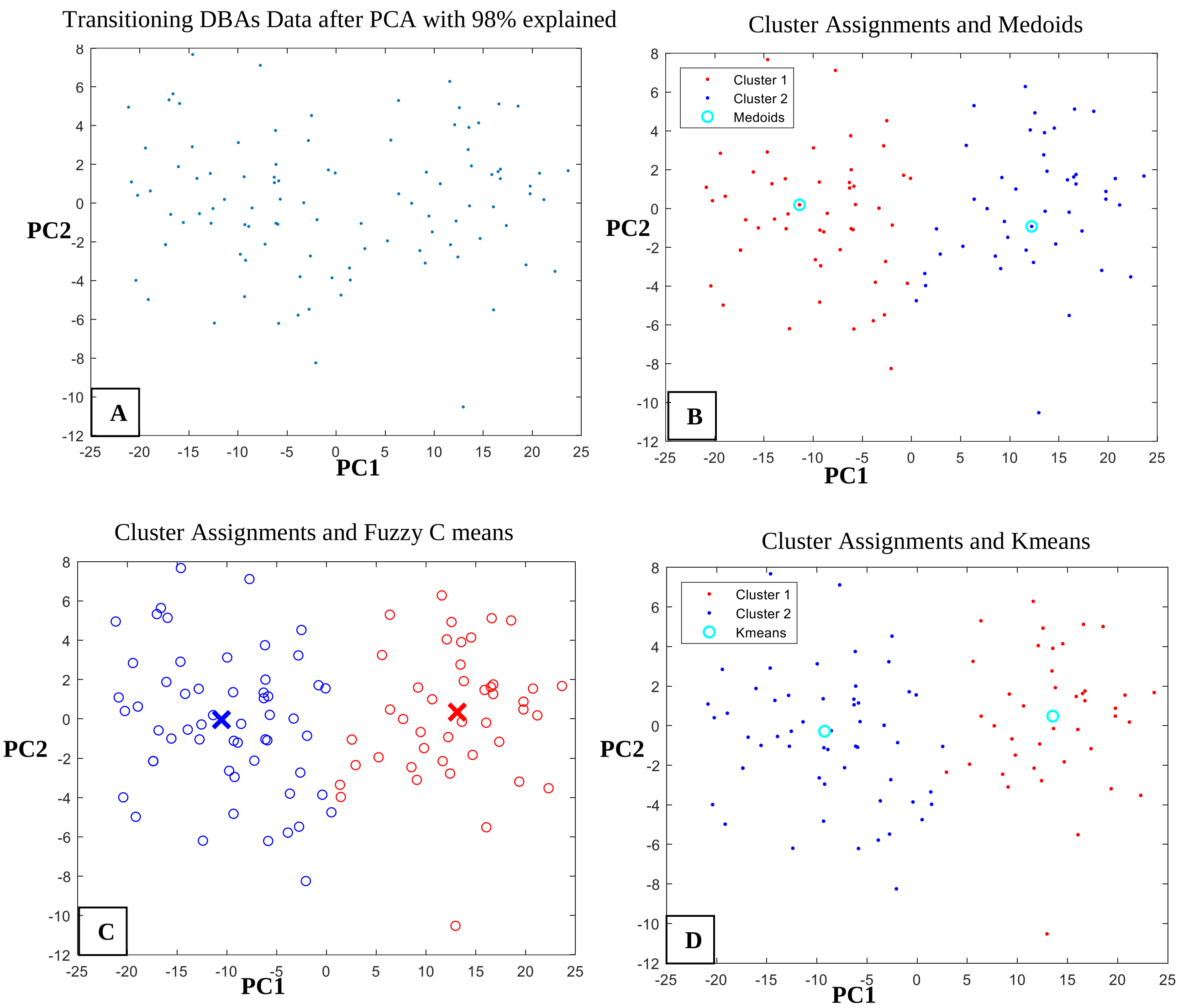


Figure 65. Clustering of transitioning DBAs data “A” using Kmedoids “B”, Fuzzy C means “C”, and Kmeans “D”

3. Results of Clustering Animated DBAs data

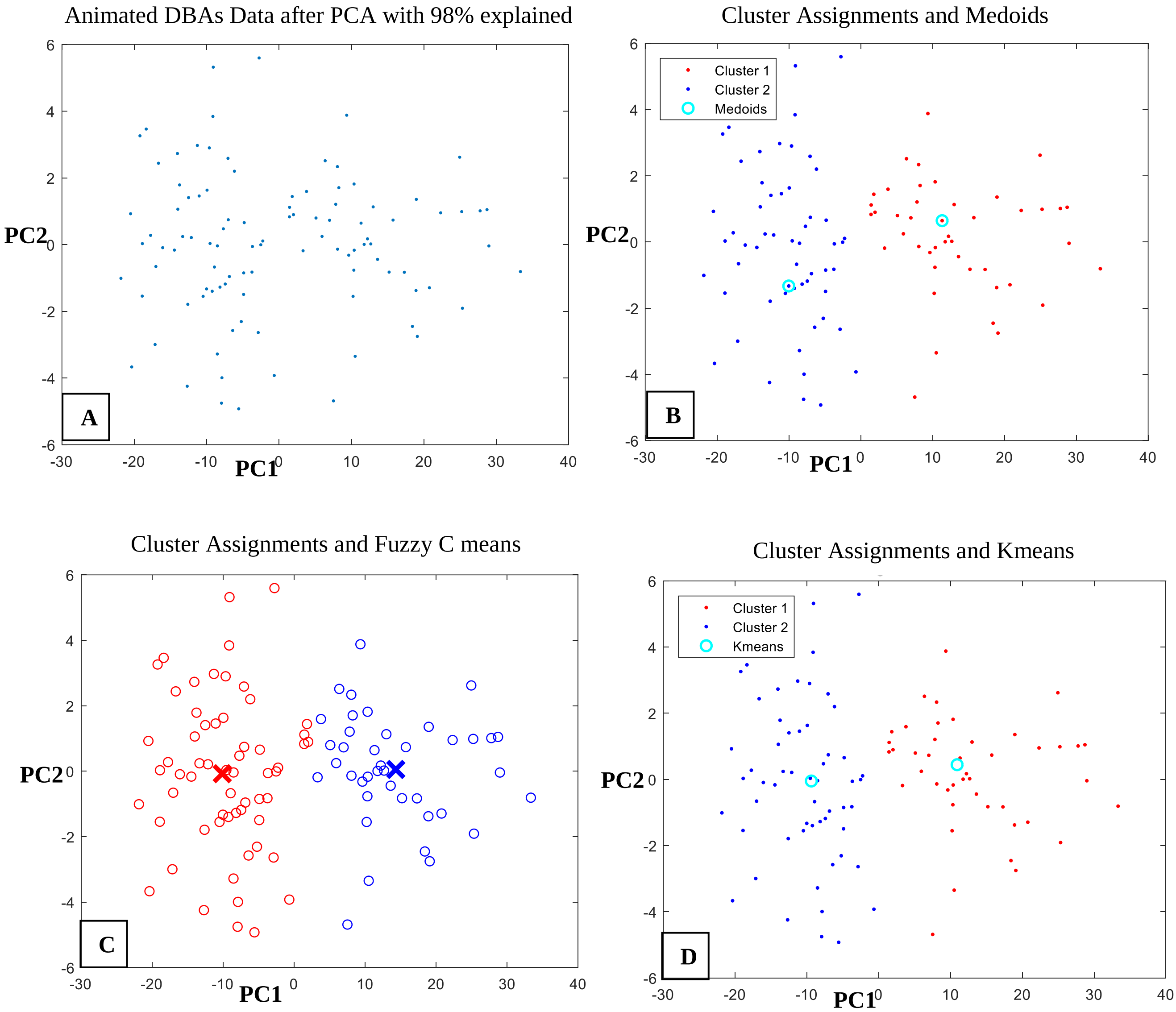


Figure 66. Clustering of animated DBAs data “A” using Kmedoids “B”, Fuzzy C means “C”, and Kmeans “D”

E. Results of Feature Importance

1. Results of the Feature Importance in the Static DBAs data

Table 19. The Feature Importance in the Static DBAs Data

Features	**Feature Importance**
Average Speed	0.0001
Average Acceleration/ Deceleration	0.0002
Average Deviation from the Center of the Lane	0.0005
Average Reaction to Traffic Lights	0.0004
Average % Fixation on the Road	0.0021
Average % Fixations on the DBA	0.0022
Average Fixations Durations on DBA	**0.0041**
Average Number of Gazes on DBA	0.0035
Average EEG Theta Band Power	0.0023
Average EEG Alpha Band Power	0.0000
Average EEG Low Beta Band Power	0.0003
Average EEG High Beta Band Power	0.0000
Average EEG Gamma Band Power	0.0001
Gender	0.0000
Age	0.0000
Years of Driving Experience	0.0000

The average fixations durations on DBA has the most impact on the detection of distraction. Following that were the average number of gazes on the DBA, the average EEG theta band power, the average % fixations on the DBA, the average % fixations on the road. On the other hand, the average EEG alpha high beta band power, the gender, the age, and the years of driving experience showed importance 0, which means that these features have no impact on predictions for distraction in the static DBAs data.

2. Results of the Feature Importance in the Transitioning DBAs data

Table 20. The Feature Importance in the Transitioning DBAs Data

Features	Feature Importance
Average Speed	0.0002
Average Acceleration/ Deceleration	0.0003
Average Deviation from the Center of the Lane	0.0014
Average Reaction to Traffic Lights	0.0021
Average % Fixation on the Road	0.0034
Average % Fixations on the DBA	0.0044
Average Fixations Durations on DBA	**0.0052**
Average Number of Gazes on DBA	0.0037
Average EEG Theta Band Power	0.0022
Average EEG Alpha Band Power	0.0001
Average EEG Low Beta Band Power	0.0015
Average EEG High Beta Band Power	0.0000
Average EEG Gamma Band Power	0.0002
Gender	0.0000
Age	0.0000
Years of Driving Experience	0.0000

The average fixations durations on DBA has the most impact on the detection of distraction. Following that were the average % of fixations on the DBA, the average number of gazes on the DBA, the average % fixations on the road, and the average EEG theta band power. On the other hand, the average EEG high beta band power, the gender, the age, and the years of driving experience showed importance 0, which means that these features have no impact on predictions for distraction in the transitioning DBAs data.

3. Results of the Feature Importance in the Animated DBAs data

Table 21. The Feature Importance in the Animated DBAs Data

Features	Feature Importance
Average Speed	0.0003
Average Acceleration/ Deceleration	0.0000
Average Deviation from the Center of the Lane	0.0010
Average Reaction to Traffic Lights	0.0033
Average % Fixation on the Road	0.0046
Average % Fixations on the DBA	0.0054
Average Fixations Durations on DBA	0.0058
Average Number of Gazes on DBA	**0.0067**
Average EEG Theta Band Power	0.0039
Average EEG Alpha Band Power	0.0001
Average EEG Low Beta Band Power	0.0011
Average EEG High Beta Band Power	0.0003
Average EEG Gamma Band Power	0.0002
Gender	0.0000
Age	0.0000
Years of Driving Experience	0.0000

The average number of gazes on the DBA has the most impact on the detection of distraction. Following that were the average fixations durations on DBA, the average % of fixations on the DBA, the average % fixations on the road, and the average EEG theta band power. On the other hand, the average acceleration/ deceleration, the gender, the age, and the years of driving experience showed importance 0, which means that these features have no impact on predictions for distraction in the animated DBAs data.

CHAPTER VIII

RESULTS OF POST-EXPERIMENT SURVEY

To have a better idea about the driving experience of the participants, they were asked about the number of days per week and the number of hours per day they usually spent driving. The number of days driving per week reported was 5.25±1.53 with 1.82±0.81 hours of driving.

16 participants reported that they had road accidents in the past 3 years. 2 cases of those were a result of technical problems with the vehicles they were driving. 5 cases were due to speeding and losing control of the vehicles. 4 cases involved being visually distracted while using mobile phones while driving. 4 cases stated that the driver did not pay attention to or did not see other vehicles or pedestrians in the surrounding.

96% of the participants answered “Yes” to the question “have you ever been distracted while driving. The participants were given options to choose from to answer the question: “what types of distraction were they?” they were allowed to check more than one answer. 50 participants checked “Use of mobile phone or other gadgets in the car”, 34 participants checked “Speaking with passengers with you in the car”, 37 participants checked “Close vehicles or pedestrians”, 35 participants checked “Advertisements placed on the road”, and 68 participants checked “Having your mind occupied with something other than the task of driving”.

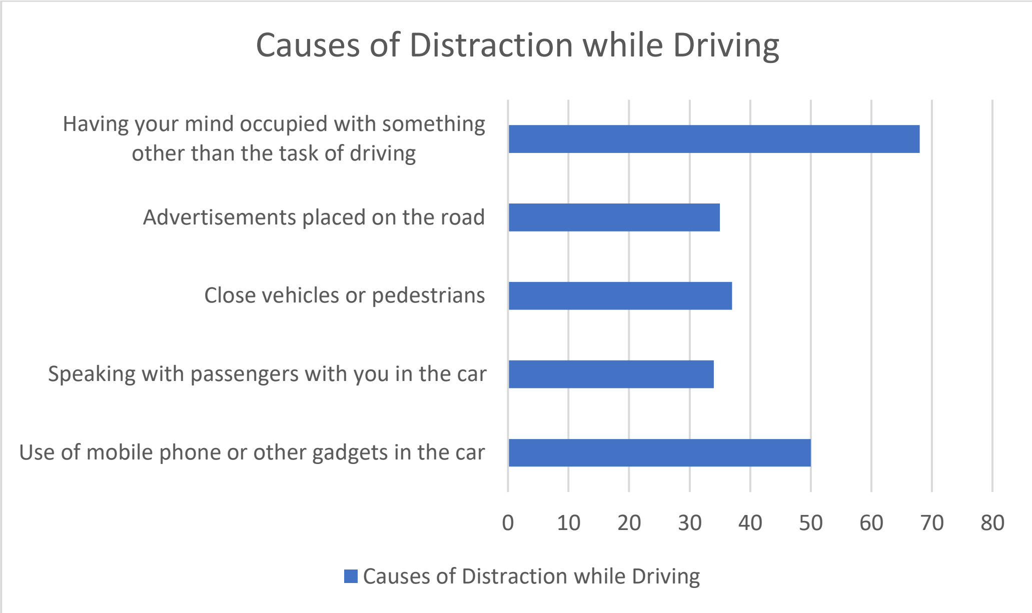


Figure 67. Causes of distraction while driving reported by the participants.

When participants were asked if they were distracted by the DBAs placed in the scenario, 10% checked the answer “No”, 53% checked the answer “A little”, and 37% checked the answer “Very much”.

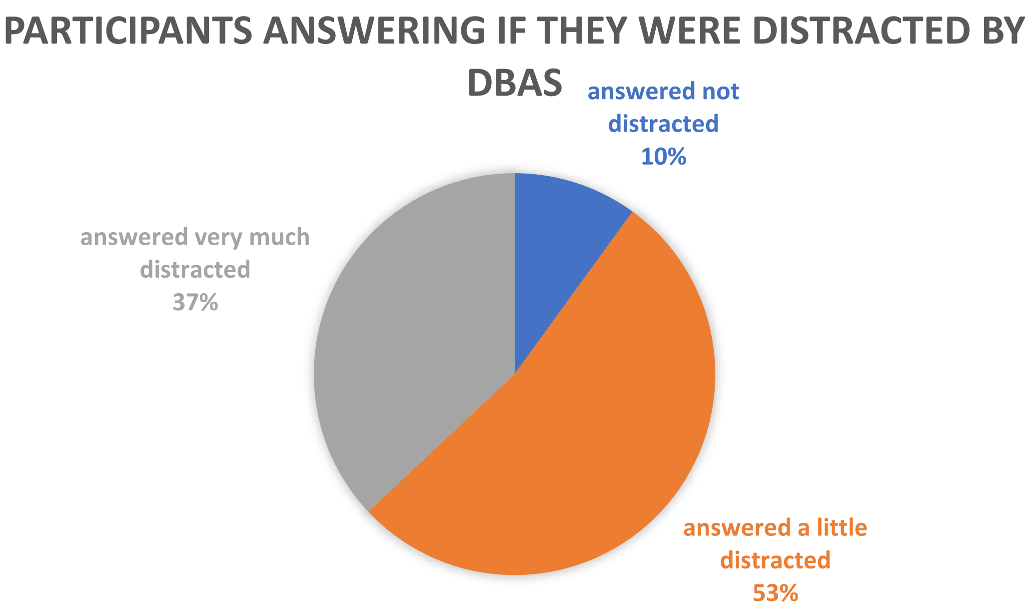


Figure 68. Overall subjective answers for distraction

It was explained to the participants that there were three formats for the DBAs. Then they were asked to order the formats of DBAs from the least they liked to the most they liked, 12% ordered the formats “animated, static, and transitioning”, 17% ordered the formats “transitioning, static, and animated”, 7% ordered the formats “ static, animated, transitioning”, 64% ordered the formats “static, transitioning, and animated”.

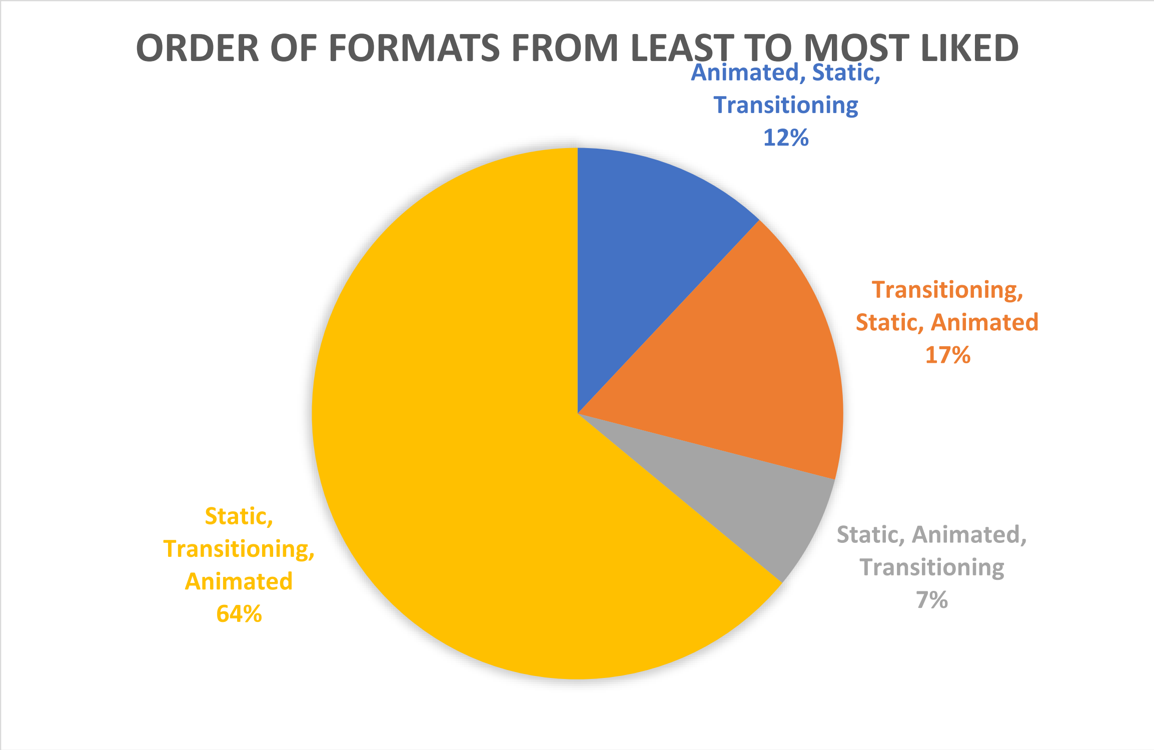


Figure 69. The order of formats liked by the participants

29% of participants answered that they did not feel dizzy while driving in the driving simulator whereas 71% reported that they felt a little dizzy during the drive but they didn’t think that the slight dizziness that they felt affected their driving behavior during the driving simulation experiment. In addition, all of the participants reported that they did not think that the placement of the sensors: Eye Tracker and the EEG affected their overall driving behavior during the experiment.

CHAPTER IX

DISCUSSION AND CONCLUSION

A. Summary of Findings

The goal of this research study was to determine the effect of different formats of DBAs on the drivers' performance and attention. The hypothesis was that each format had different levels of detrimental effects on driving behavior and attention.

The statistical analysis performed in this study concludes that the three formats of DBAs interfere differently with driving performance, visual behavior and the EEG frequency bands powers of drivers. These results show that the driving performance and attention to the road were both affected more negatively when drivers were exposed to transitioning and animated DBAs. This conclusion can be validated by the results of animated DBAs leading to the highest deviation from the center of the lane, reaction time to traffic lights, % fixations, fixation duration, and highest power in the theta and lowest in the beta bands of the frontal cortex. On the other hand, transitioning DBAs caused the highest number of gazes on the DBAs, which suggests that transitioning DBAs demanded more frequent gazes than animated DBAs which demanded more fixation duration, perhaps because drivers in the experiment were anticipating the appearance of the next advertisement in transitioning DBAs but whilst in animated DBAs they had longer fixations watching the short video with less frequent gazes. Furthermore, the fact that there was no significant effect of the different formats of DBAs on the average speed, average acceleration, and average deceleration suggests that drivers do not necessarily slow down significantly when they see a DBA while driving.

The statistical analysis of the difference in the power of EEG frequency bands correlate with findings in the literature which state that the power of the theta band and beta band of the frontal cortex are indicative of distraction. There were no significant statistical differences found in the other power of EEG frequency bands. This could be explained by the fact that the experiment that the participants drove through did not require a very high workload.

The results of the classification models based on different labeling schemes demonstrated that using PCA with 98% explained variance and machine learning clustering technique achieved the highest accuracy in classification between “distracted” and “not distracted” compared to the statistical methods for labeling distraction (L1, L2, and L3).

The overall results of the feature importance prediction suggest that the eye tracking metrics were the most contributing features to the detection of drivers' distraction caused by DBAs, following those features were the theta EEG band power, the reaction time to traffic lights, and the deviation from the center of the lane. Other factors such as gender, age, and driving experience appeared to be relatively insignificant in the predictions for distraction, which means that the data was not biased towards gender, age, and driving experience.

B. Contributions

The results of this study contribute to a better understanding of the impacts of different formats of DBAs placed on the road on drivers’ driving performance, visual attentiveness to the road, and EEG dynamics.

The effects of the transitioning DBAs appeared to be statistically more detrimental than static DBAs when it came to the average deviation from the center of the lane, the average % of fixations on the road and DBAs, the average fixation durations, and the average number of gazes. Whereas in [5] the transitioning DBAs did not show the expected more significant effects than the static DBAs, this is probably due to the simple design of the DBAs which were designed as logos and taglines for companies and the transitioning DBAs were programmed to change only once.

The results of this study correlate with the eye tracking results obtained in [11] and [15] which studied the effects of the presence of transitioning DBAs versus the absence of DBAs. In [11] a significant shift was reported in the number and length of glances toward the transitioning DBAs and an increased percentage of time glancing off the road in the presence of the transitioning DBAs. In [15] results show significantly longer fixation durations, a more significant number of gazes, and longer maximum fixation duration when driving saw transitioning DBAs, however, there were no effects found in the driving performance. In our study, the presence of transitioning DBAs lead to increased deviation from the center of the lane, increased reaction time to traffic lights, decrease in the % fixations on the road, and a change in the powers of both the theta and beta EEG frequency bands of the frontal cortex which as shown in [24, 25, 29] provide evidence for drivers' cognitive distraction.

Using the L4 labeling technique based on the clustering of the data after PCA with 98% explained variance resulted in higher accuracies in the classification of “distracted” and not “distracted” compared to the statistical methods L1, L2, and L3 used in [20, 44].

The findings of this research recommend that policymakers should look into the differences in the effects of static and transitioning/ animated DBAs when it comes to drivers' distraction and should not approve the placement of the DBAs randomly or the same way as the conventional static DBAs. Given the different levels of distraction that each format of DBA poses, proper legislation should be made as to where each of these DBAs is allowed to be placed and where they should be banned. Considering the high visual and cognitive distraction and the deterioration in driving performance that transitioning and animated DBAs caused, these types of DBAs would pose a significant danger if placed in highways or locations with a high number of pedestrians and uncontrolled pedestrian crossings such as schools, shopping malls, and touristic places.

On another note, the automobile manufacturers believe that the implementation of self-driving cars promises life-changing road safety by decreasing car accidents caused by human error [53]. However, smart cities have yet to become widespread and be ready to accommodate fully autonomous vehicles efficiently. Therefore, the automotive industries, for the time being, will have to cater to two kinds of settings: smart cities that are suitable for fully autonomous vehicles, and traditional cities which can use for the time being semi-autonomous vehicles. These semi-autonomous vehicles would intervene only when necessary to prevent the occurrence of road accidents. Inputs for such a system could be physiological signals, driving performance recordings, or eye positions and movements. Implementing semi-autonomous vehicles which should understand and interact naturally with human drivers can help with the gradual penetration of fully autonomous cars technology in regions that have yet to mature to be able to comply with such automation. The significant differences in the impact of each format of DBA captured in this research indicate that research for semi-autonomous vehicles should account for the different formats of DBAs. Moreover, the real-time detection of drivers' distraction could use the features that have shown relation to distraction for an intelligent in-vehicle device that could detect distraction and alarm the driver or switch to self-driving mode in semi-autonomous vehicles.

C. Limitations of the Research Project

One major limitation in this research was not covering other aspects of DBAs such as brightness [15], colors, content, text, locations, and sizes of DBAs, some of which were investigated in the literature. Analyzing these other aspects was not possible in this study due to the limitation in the instrumentation that was available to us. If these aspects were included in the experiment, more variables related to the DBAs would be available to study and thus we would have many combinations of characteristics for DBAs which would resemble real-life DBAs that we might see in an urban setting. Moreover, we would be able to analyze the different combinations of DBAs' traits and their adverse impact on the attention and performance of drivers. With that, we would be able to give a more detailed recommendation for the guidelines for designing and placement of DBAs for authorities to consider to decrease the risk of distractions caused by DBAs and improve the overall road safety.

D. Recommendations for Future Research

Additional driving performance, eye tracking, and EEG features that could contribute to distraction should be further investigated. Furthermore, data collection could be extended to increase the sample size and include older age groups and the general population rather than only AUB community. This study analyzed the data as a whole, while studying the data event by event individually or in a personalize aspect would also be interesting and would yield results based on individual profile.

This study analyzed data before and during the appearance of DBAs. The effect of the different formats of the DBAs on drivers' performance and attention may also be analyzed after the drivers get past the DBA to have an idea if the detrimental effects continue after getting past the DBA, and if they do continue, how long they would keep affecting the drivers' performance and attention.

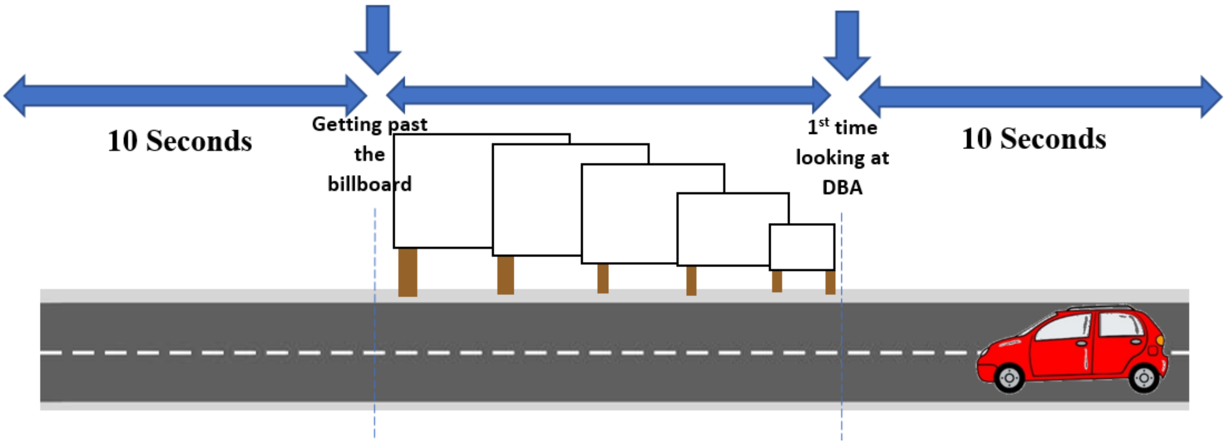


Figure 70. Proposed research to analyzing effects after getting past DBAs

As for the prediction model, future extensions for this research should proceed towards the detection of drivers' distraction in real-time. The challenges in that course is extracting meaningful features during a short window of time to be able to alert the driver or switch the semi-autonomous vehicle to self-driving mode on time minimizing the risk of the occurrence of car crashes. The system would include sensors from the vehicle, eye tracking sensors and EEG sensors.

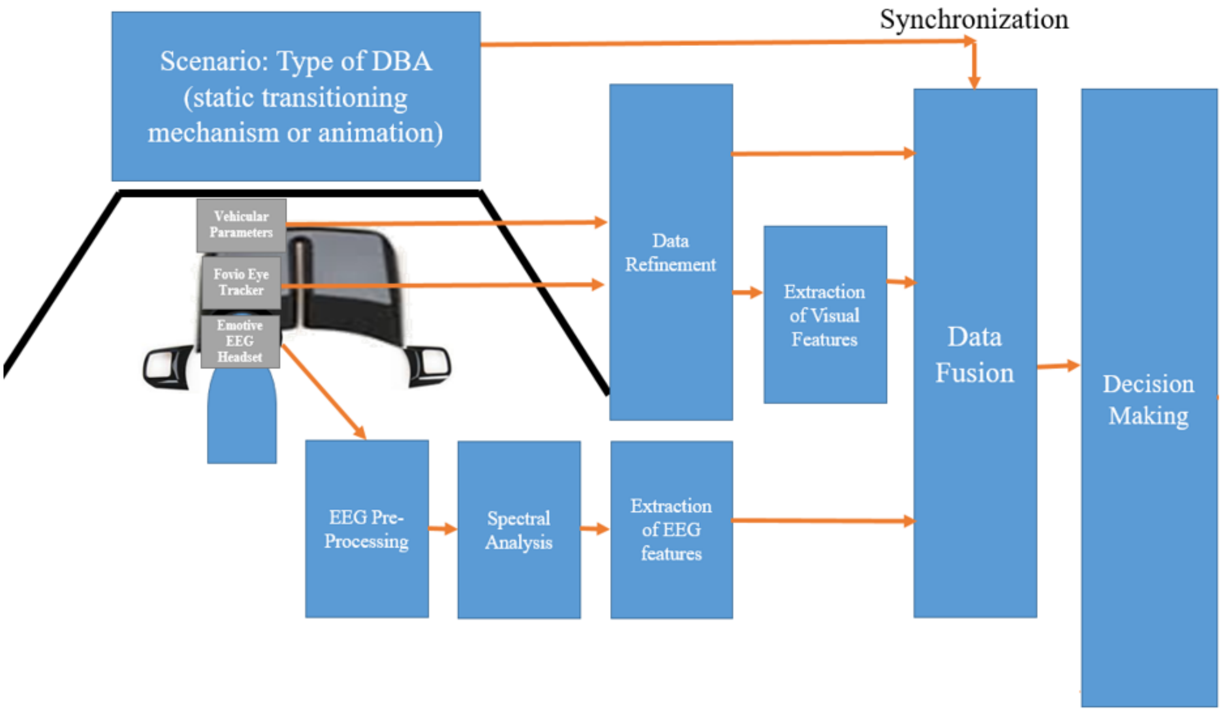


Figure 71. Proposed system for real-time detection of drivers' distraction

EEG can be worn as a wireless headband that can be easily worn and some are readily available in the market nowadays such as the one used in this study and others shown in the following figures.

The EMOTIVE Insight [54] 5 channel (AF3, AF4, T7, T8, Pz , and two reference electrodes) mobile EEG costs around $300 is mainly used for the research field and brain-computer interface. The BrainLink Pro [55] is an EEG wireless headband that is designed to comfortably monitor the mental wellness of users as the headband-style design can easily be adjusted to fit the user’s head with dry EEG electrodes. These features make it easier for users to wear this EEG headband for long durations of time. This device costs around $100 and with it many mobile apps are unlocked to use them for meditation purposes and monitoring mental health. The Muse – Brain sensing headband [56] costs around $200. It is also a wireless headband that allows 6 hours of continuous monitoring with a rechargeable battery. Its application is similar to that of the BrainLink Pro EEG headband which is intended to monitor the user’s EEG and accordingly help with meditation and mental wellbeing by playing music as a feedback to the monitored EEG to help the user reach the state of relaxation. This device can be used as a full guidance that walks the user through how to meditate and to record and monitor EEG without any guidance.

Figure 72. EMOTIV Insight 5 Channel Mobile EEG [54]

Figure 73 The BrainLink Pro [55]

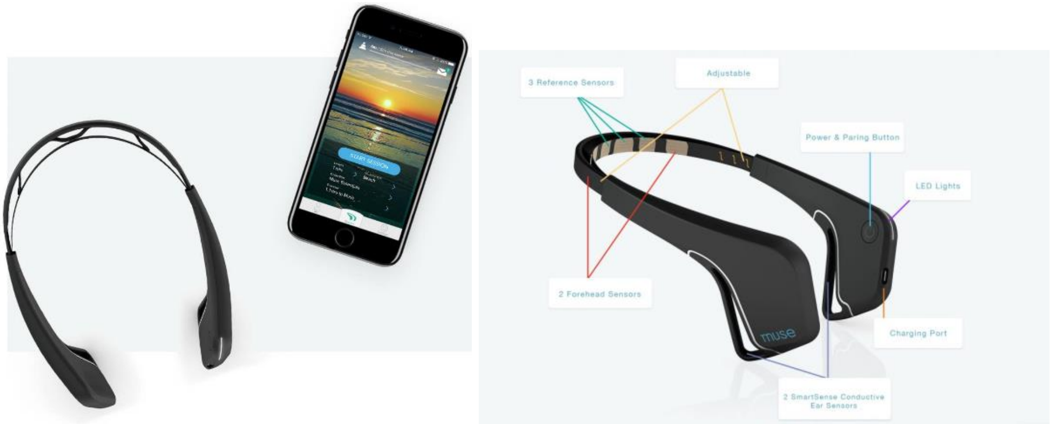


Figure 74. Muse – The Brain Sensing Headband [56]

I. APPENDIX A: Static DBAs


Sandra's Fashion Bags
Call us: 5324
JES


Walk with High Style
Call us: 2377
LET


Stand Out with these
Call us: 8973
FEB


Get a New Red Car
Call us:
6349
LUK


It is time for a change
Call us:
7582
ANF


Coming your way
Call us:
2315
LUK

III. APPENDIXB: Transitioning DBAs


You know you need it
Call us:
3031
KRA


Spoil yourself today
Call us:
4527
MCR


Magic and pasta
Call us:
3671
LIZ


Everyday casual
Call us:
6396
HOD

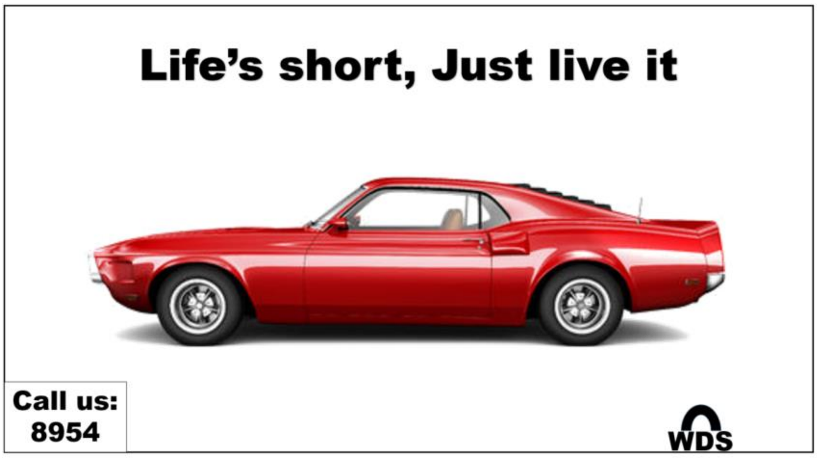

Complete your look
Call us:
6391
KYR


Dress to impress
Call us:
5624
JAM


Details do matter
Call us:
6294
GHA


Stand out in a crowd
Call us:
8732
OBO


Stay cozy all winter
Call us:
7521
FLO


Life's short, Just live it
Call us:
8954
WDS


Make a lastin' impression
Call us:
1230
LAS


You know you want it
Call us:
4265
MEW

Time to show it off

Call us:
8155

TIR

Drive with Pride

Call us:
6253

JUL

Are we there yet?

Call us:
7849

LPX

III. APPENDIX C: All Documents related to Data Collection

Information Sheet

Principal Investigator: Prof. Mariette Awad

Co-Investigators:

- Prof. Nadine Marie Moacdieh
- Reem Abou Marak/ Brome

Address: Irani Oxy Engineering Complex (IOEC)

American University of Beirut

Bliss Street

Beirut, Lebanon

Phone: (01) 350 000

A. Project Description

1. In this study, you will be asked to drive in a simulated environment similar to the streets in Beirut, Lebanon. Your driving performance, visual behavior, and brain activity will be recorded noninvasively as a means of evaluating your driving behavior. Please note that there will be no video recording nor microphone recording during the experiment.

2. The estimated time to complete this experiment is approximately 40 minutes.

3. This research is being conducted as part of a masters' thesis research.

4. Signing the consent form will take place before the experiment in the Transportation and Infrastructure Research Laboratory (IOEC 125). The experiment will take place in the Transportation Driving Simulator (IOEC 124).

5. The sample size for this study is 100.

B. Participant/subject recruitment and selection

100 volunteers are expected to take part in the experiment. The participants will include AUB students and staff. A screening interview before the start of the driving session is performed to make sure that the participant is qualified to participate. The inclusion criteria for participation:

- English literate
- age above 18
- owns a driver's license

- AUB student or staff
- good physical and mental health
- Not taking medication such as sedatives and tranquilizers, muscle relaxants, and sleeping aids.

Participants will be informed about the research experiment and the need for volunteers through emails, flyers distributed across campus, and announcements during classes.

C. Inclusion/Exclusion criteria

You are eligible to participate in this research study if you are an AUB student or staff (aged above 18), have a driving license, and are currently driving.

You are not allowed to drive the simulator if you suffer from at least one of the following health-related issues:

- If you are on medications
- If you have ever complained of dizziness
- If you have an ear or eye problem
- If you have any motion sickness
- If you had any recent sleep deprivations
- If you have any active medical problems such as heart problems, epilepsy, respiratory problems, etc.
- If you have any active medical problems such as anxiety, panic disorder, etc.
- If you have a fear of being enclosed in a small space or room and having no escape
- If you have Alzheimer's disease
- If you have any mental health condition that would make you feel uncomfortable participating in this experiment
- If you currently feel exhausted

D. Risks and Benefits

Your participation in this study does not involve any physical risk or emotional risk to you beyond the risks of daily life. You have the right to withdraw your consent or discontinue participation at any time for any reason. Your decision to withdraw will not involve any penalty or loss of benefits to which you are entitled. Discontinuing participation in no way affects your current or future relationship with the American University of Beirut (AUB).

The benefits of this study include helping to understand drivers' behavior and improve road safety.

E. Confidentiality

To secure the confidentiality of your responses, your name, and other identifying information will never be attached to your answers. The data in this study will not contain any identifiers at all other than your age. Your privacy will be maintained in all published and written data resulting from this study. Your name or other identifying information will not be used in reports or published papers resulted from this study. Data will be stored for three years after the study completion in the Transportation and Infrastructure Research Laboratory (Irani-Oxy Engineering Complex), which is accessible only by the project researchers.(3 years) Passwords are used on the PC's were the data will be analyzed. Data will be monitored and may be audited by the IRB while assuring confidentiality.

F. Experimental Setup

A screening interview will first be performed with the participant to make sure that they are eligible to participate in the experiment. This interview includes questions related to their medical profile and their driving records. Once it is confirmed that the participant is eligible to participate, he/she fills a consent form and a demographics survey to record information about his/her age, gender, and years of experience in driving while keeping their profiles as anonymous. The participant then undergoes the procedure of EEG electrodes placement on his/her scalp and any required procedure of calibration of the EEG instrumentation and Eye Tracker device. The participant is seated in the driver's seat of the partial cab and is introduced to the driving simulator and instructed to obey road signs and follow the vocal directions. Once everything is in place, and all the sensors are attached properly, the participant drives through a track similar, yet less challenging than the actual experiment, in order to get accustomed to the vehicle's control system. All of the procedure mentioned so far is with the experimenter's guidance and is expected to take around 15 minutes. The actual experiment is expected to last around 20 minutes. After the driving experiment, the participants are asked to sign the debriefing form and fill a post-experiment survey asking them various question among which are: which advertisements they remember and their assessment of their performance and attention throughout each section of their drive.

G. Safety of the Eye Tracker and EEG

The eye tracker used is an infrared-based, desktop mounted system, meaning that it is placed in front of the user with nothing in contact with the user at all. The system emits infrared light and uses cameras to track where a person is looking. There is thus no risk at all of harm to the participant. The EEG headset which is completely noninvasive and poses no risk on the patient. Both devices have been tested by the manufacturer and engineers at AUB/ AUBMC and confirmed to be safe for use.

H. Risks

This study does not subject the participants to any physical or emotional risks beyond the risks of daily life. The risks associated with the experiment (dizziness) are minimal, and the experiment session will be terminated immediately if a participant decides not to proceed or suffers dizziness.

I. Contact Information

1) If you have any questions or concerns about the research, you may contact the P.I. Prof. Mariette Awad (ma162@aub.edu.lb, AUB Ext: 3528).

2) If you have any questions, concerns, or complaints about your rights as a participant in this research, you can contact the following office at AUB: Social & Behavioral Sciences Institutional Review Board (irb@aub.edu.lb, AUB Ext: 5445).

J. Participant Rights

Participation in this study is voluntary. You are free to discontinue your participation at any time without penalty. Your decision not to participate or to discontinue your participation will not influence your current or future relationship with the American University of Beirut (AUB).

I have read and understood the above information. All my related questions have been answered. I voluntarily agree to participate in the research study. I am aware that I will receive a copy of this signed informed consent.

Participant Reference Number: ____________________ Date: ________________________

Investigator: ______________________________________ Date: ________________________

Thank you for your participation.

Screening Interview to Participate in a Research Study

Subject ID: ___________________________________

Interview Date:________________________________

The below questions are asked to confirm that you are qualified to participate in this study and to gather information for statistical analysis.

1. Do you have a driver's license?
   ☐ Yes
   ☐ No

[*If "No", the participant is to be told that he/she is not eligible to participate in the study; otherwise, the participant is politely asked to show his/her driver's license to proceed later with the next questions.]*

2. Have you ever participated in a driving simulation experiment?
   ☐ Yes
   ☐ No

3. Do you currently drive?
   ☐ Yes
   ☐ No

[*If "Yes", interviewer proceeds to Question 3a; if "No", interviewer proceeds to Question 3b*.]

3a. for how long have you been driving?

____

3b. how long has it been since you stopped driving?

____

[if the participant stopped driving more than 2 years ago, the participant is to be told that he/she is not eligible to participate in the study]

4. What type of roads do you drive more often?
   ☐ Highway
   ☐ Urban (city driving)
   ☐ Rural

5. Where do you usually drive?
   ☐ Lebanon, Greater Beirut
   ☐ Lebanon, Outside Greater Beirut
   ☐ Outside Lebanon. Please Specify ________________________

6. [Health related questions]

6a. Are you on any type of medication?

☐ Yes
☐ No

[*if the type of medication is mentioned in the list of medications that are under exclusion, interviewer thanks the participant and tells him/her that he/she is not eligible to participate in the study; otherwise, interviewer proceeds to Question 6b.*]

6b. Have you ever complained of dizziness?

☐ Yes
☐ No

6c. Do you have any ear or eye problem?

☐ Yes
☐ No

6d. Do you suffer from motion sickness?

☐ Yes
☐ No

6e. Have you had any recent case of sleep deprivation (i.e. sleeping for less than 6 hours a day/ having a sleeping disorder causing poor quality of sleep)?

☐ Yes
☐ No

6f. Do you have any active medical problems such as heart problems, epilepsy, respiratory problems, etc.?

☐ Yes
☐ No

6g. Do you have any active psychiatric problems such as anxiety, panic disorder, etc.?

☐ Yes
☐ No

6h. Are you claustrophobic (fear of being enclosed in a small space or room)?

☐ Yes

☐ No

6i. Do you have Alzheimer's disease?

☐ Yes
☐ No

6j. Do you have any mental health condition?

☐ Yes
☐ No

6k. Do you currently feel exhausted?

☐ Yes
☐ No

6l. Have you had a main meal shortly before coming to the experiment?

☐ Yes
☐ No

[*If subject answers "Yes" to any of the questions 6b to 6l, interviewer thanks the participant and tells him/her that he/she is not eligible to participate in the study; otherwise, interviewer proceeds to Question 7.*]

7. [Interviewer notes respondent's gender.]
   ☐ Male
   ☐ Female

[*If "female", the interviewer asks the participant question 8; otherwise, interviewer proceeds to Question 9.*]

8. Are you pregnant?
   ☐ Yes
   ☐ No

[*If "No", the participant is to be told that she is not eligible to participate in the study; otherwise, interviewer proceeds to Question 9.*]

9. How old are you? ______________________

[*If the participant is younger than 18 years old, the interviewer tells him/her that he/she is not eligible to participate in the study.*]

10.

10a. what is your occupational status?

☐ Student at AUB
☐ Employee at AUB
☐ Other. Please
specify____

10b. if a student, what are your faculty and major study?

Faculty____

Major of study____

10c. if a student, what is your current educational status?

 Sophomore (first year)
 Junior (second year)
 Senior (third year or above)
 Graduate (Masters or Ph.D. student)

10d. if an employee, what is your job type?

 Academic
 Management
 Non-academic, non-management. Please specify ______________________________

Post Driving Survey for a research study

This survey is intended to study the driving behavior of the participants and their opinions about driving safety. All your answers will remain confidential.

Subject ID [Filled out by Research Assistant]: ……………

Survey Date and Time [Filled out by Research Assistant]: ……………

Please answer each of the following items as honestly as possible. Please read each question carefully and then select or write down the answer. If none of the choices seems to be your ideal answer, then choose the answer that comes closest. THERE ARE NO RIGHT OR WRONG ANSWERS. Select your answers quickly and do not spend too much time analyzing your responses. The expected completion time of this survey is less than 5 minutes.

Section I: Experience in the Driving Experiment

The following questions are about the driving experience you just went through using the simulator with the EEG headset and the Eye tracker device.

1. Do you think the advertisements placed on the road caused any distraction to you while driving in the experiment?

Not at all	A little	Very much
☐	☐	☐

2. What billboard advertisements do you remember seeing during the driving experiment?
____
____
____
____
____
3. What advertisements were you drawn to the most?
____
____
____
____
____

4. Which advertisements did you like most, not in terms of content but rather in terms of the mechanisms (how they are transitioning and whether they

are static or dynamic? Please number from 1 to 4, with **1** being the least liked and **4** being the most liked.

__Static Advertisements
__ Instantly Transitioning Static Advertisements
__ Gradually Transitioning Static Advertisements
__Animation advertisements

5. To what extent did you feel dizzy while driving the simulator?

Not at all	A little	Very much
☐	☐	☐

6. Do you believe that dizziness or other factors affected your driving behavior in the simulator to differ from your actual driving behavior on the roads?

Not at all	A little	Very much
☐	☐	☐

7. To what extent do you think did the attachment of the EEG headset and the Eye tracker affect your behavior while driving?

Not at all	A little	Very much
☐	☐	☐

Section I: Driving Experience

1. How many hours do you typically drive on an average weekday?

    ____

2. How many days per week do you drive on average?

    ____

3. How many major accidents in the past 3 years have you been involved in as a driver? ________________

4. What were the causes of these accidents?

    ____
    ____
    ____
    ____
    ____

5. Were you ever distracted while driving?

□ Yes
□ No

If yes, what types of distractions were they? (You can choose more than one answer)
□ Use of mobile phone or other gadgets in the car
□ Speaking to passengers with you in the car
□ Close vehicles or pedestrians
□ Advertisements placed on the road
□ Having your mind occupied with something other than the task of driving

Other: ____

6. What types of industries in advertisements interest you?

□ Sports

□ Food and beverage

□ Cars

□ Fashion

□ Real Estate

□ Bank facilities and loans

□ Movies/ Cinema

□ Electronic devices and gadgets

□ Music

□ Travel

Other: ____

7. Please write down any comments about this survey or the driving experiment:
____
____
____
____
____

Thank you for your participation.

<u>Debriefing Form</u>

Digital Billboards Advertisements' Effects on Drivers' Performance and Attention

<u>Subject ID</u> [Filled out by Research Assistant]: ………………………………

Investigator: <u>Prof. Mariette Awad</u>
Address: American University of Beirut
Department of Electrical and Computer Engineering
Riad El-Solh / Beirut 1107 2020, Lebanon
Phone: (01) 350 000 ext ____3528__
Email: ma162@aub.edu.lb

This project aims at analyzing the effects of different mechanisms for transitioning static digital billboard advertisements (DBAs) and the effects of animated video format DBAs on drivers' performance and attention by the evaluation different parameters. These parameters include vehicular parameters, visual behavior, and time-frequency brain activity. The results will serve in structuring a recommendation for regulating the way advertisements are displayed on digital billboards to minimize accidents caused by driver distraction which is expected to increase road safety. Please note that refusal or withdrawal from the study will involve no loss of benefits to which you are otherwise entitled nor will it affect your relationship with AUB.

By signing this form, you are agreeing on using the collected data for analysis to meet the research objectives.

Thank you for your participation and cooperation.

Investigator's Statement:

I have reviewed, in detail, the debriefing document for this research study with ___ _______________________________ (name of participant) the purpose of the study and its risks and benefits. I have answered to all the participant's questions clearly. I will inform the participant in case of any changes to the research study.

Mariette Awad _________________

Name of Investigator or designee **Signature**

____

Date

American University of Beirut, Riad El-Solh / Beirut 1107 2020, Lebanon

Participant's Participation:

I have read and understood all aspects of the research study and all my questions have been answered. I voluntarily agree to be a part of this research study and I know that I can contact Prof. Mariette Awad at 01-350000 Ext. 3528 or by email (ma162@aub.edu.lb) or any of her designee involved in the study in case of any questions. If I feel that my questions have not been answered, I can contact the Institutional Review Board for human rights at 01-350000 Ext. 5440. I know that I will receive a copy of this signed document.

Name of Participant **Signature**

Date

List of Medications under Exclusion

Below is a list of medications that are under exclusion for the research study. It is intended to be a reference for the interviewer in order to decide whether the subject is eligible to participate in the study as judged by the type of medications he/she takes. That is, if the subject's answer to question 6.a is "yes", he/she will have to specify the medication. Interviewer will check if the specified medication is mentioned in the list below, and will decide if the subject is eligible to participate accordingly.

Dizziness, Vertigo, and Imbalance Medications

a) Antihistamines, 1st Generation

- Meclizine (Antivert, Medi-Meclizine, Trav-L-Tabs)
- Dimenhydrinate (Dramamine, Driminate, Triptone)

b) Anxiolytics, Benzodiazepines

- Diazepam (Valium, Diastat)

c) Phenothiazine Derivatives

- Promethazine (Phenergan, Phenadoz, Promethegan)
- Prochlorperazine (Compro)

d) Alpha/Beta Adrenergic Agonists

- Ephedrine

e) Anticholinergic Agents

- Glycopyrrolate (Robinul, Cuvposa)
- Scopolamine (Transderm Scop)

Motion Sickness Medications

a) Anticholinergic agents

- Scopolamine (Transderm Scop)

b) Antihistamines

- Dimenhydrinate (Dramamine, Gravol, Driminate)
- Meclizine (Bonine, Bonamine, Antivert, Postafen, and Sea Legs)
- Cyclizine (Marezine, Bonine For Kids, Cyclivert)
- Promethazine (Phenergan)

c) Sympathomimetics

- Ephedrine

Sleep Deprivation Medications

a) Sedative-Hypnotics

- Zaleplon (Sonata)
- Zolpidem (Ambien, Ambien CR, Edluar, Intermezzo, Zolpimist)
- Eszopiclone (Lunesta)
- Triazolam (Halcion)
- Estazolam
- Temazepam (Restoril)
- Ramelteon (Rozerem)
- Suvorexant (Belsomra)

b) Antidepressants, TCAs

- Amitriptyline
- Doxepin (Silenor)
- Nortriptyline (Pamelor)

c) Antidepressants, Other

- Mirtazapine (Remeron, Remeron SolTab)
- Trazodone (Oleptro)

- Nefazodone

Epilepsy and Seizures Medications

a) Anticonvulsants, Other

- Carbamazepine (Tegretol, Tegretol XR, Carbatrol, Epitol, Equetro)
- Clobazam (ONFI)
- Ethosuximide (Zarontin)
- Ezogabine (Potiga)
- Felbamate (Felbatol)
- Lamotrigine (Lamictal, Lamictal ODT, Lamictal XR)
- Levetiracetam (Keppra, Keppra XR)
- Phenytoin (Dilantin, Phenytek)
- Primidone (Mysoline)
- Rufinamide (Banzel)
- Topiramate (Topamax)
- Valproic acid (Depakote, Depakote ER, Depakene, Depacon, Stavzor)
- Zonisamide (Zonegran)
- Perampanel (Fycompa)
- Lacosamide (Vimpat)

b) Anticonvulsants, Barbiturates

- Phenobarbital (Luminal)

c) Sodium Channel Blockers

- Carbamazepine (Tegretol, Tegretol XR, Carbatrol, Epitol, Equetro)
- Phenytoin (Dilantin, Phenytek)
- Fosphenytoin
- Oxcarbazepine
- Eslicarbazepine
- Lamotrigine (Lamictal, Lamictal ODT, Lamictal XR)
- Zonisamide

- Lacosamide

d) GABA Receptor Agonists

- Clobazam (ONFI)
- Clonazepam
- Phenobarbital
- Primidone (Mysoline)

e) GABA Reuptake Inhibitors

- Tiagabin

f) GABA Transaminase Inhibitors

- Vigabatrin

g) AEDs with potential GABA Mechanism of Action

- Gabapentin
- Pregabalin
- Valproat (Depakote, Depakote ER, Depakene, Depacon, Stavzor)

h) Glutamate Blockers

- Felbamate
- Topiramate
- Perampanel

i) AEDs with other Mechanisms of Action

- Levetiracetam
- Rufinamide
- Brivaracetam

Anxiety Disorder Medications

a) Selective Serotonin Reuptake Inhibitors

- Paroxetine (Paxil)
- Escitalopram (Lexapro)
- Sertraline (Zoloft)
- Fluoxetine (Prozac)
- Fluvoxamine (Luvox)

- Citalopram (Celexa)

b) Serotonin and Norepinephrine Reuptake Inhibitors

- Venlafaxine (Effexor XR)
- Duloxetine (Cymbalta)

c) Atypical Antidepressants

- Nefazodone (Serzone)
- Trazodone (Desyrel)
- Mirtazapine (Remeron)

d) Tricyclic Antidepressants

- Imipramine (Tofranil)
- Amitriptyline (Elavil)
- Desipramine (Norpramin)
- Clomipramine (Anafranil)
- Nortriptyline (Pamelor)
- Protriptyline (Vivactil)
- Doxepin (Sinequan)
- Amoxapine
- Trimipramine (Surmontil)

e) Benzodiazepines

- Alprazolam (Xanax)
- Lorazepam (Ativan)
- Clonazepam (Klonopin)
- Diazepam (Valium)
- Chlordiazepoxide (Librium)
- Oxazepam (Serax)

f) Antianxiety Agents

- Buspirone (BuSpar)

g) Anticonvulsants

- Pregabalin (Lyrica)
- Gabapentine (Neurontine)
- Divalproex (Depakote, Depakote ER)

h) Antihypertensive Agents

- Clonidine (Catapres)
- Propranolol (Inderal, Betachron E-R, InnoPran XL)
- Nadolol (Corgard)
- Atenlol (Tenormin)

i) Monoamine Oxidase Inhibitor (MAGI)

- Phenelzine (Nardil)
- Selegiline (Emsam)
- Tranylcypromine (Parnate)
- Isocarboxazid (Marplan)

j) Antipsychotic Agent

- Risperidone (Risperdal)
- Aripiprazole (Abilify)
- quetiapine (Seroquel)
- Haloperidol (Haldol)
- Clozapine (Clozaril)
- Olanzapine (Zyprexa)

Panic Disorder Medications

a) Anxiolytics, Benzodiazepines

- Lorazepam (Ativan)
- Clonazepam (Klonopin)
- Alprazolam (Xanax, Xanax XR)
- Diazepam (Valium, Diastat, Diazepam Intensol)

b) Antidepressants, SSRIs

- Fluoxetine (Prozac)
- Paroxetine (Paxil, Paxil CR, Pexeva)
- Sertraline (Zoloft)
- Fluvoxamine (Luvox, Luvox CR)
- Citalopram (Celexa)
- Escitalopram (Lexapro)

c) Antidepressants, TCA

- Imipramine (Tofranil, Toframil-PM)
- Desipramine (Norpramin)
- Clomipramine (Anafranil)

d) Antidepressants, MAO Inhibitors

- Phenelzine (Nardi')
- Tranylcypromine (Parnate)

e) Antidepressants, SNRI's

- Venlafaxine (Effexor, Effexor XR)

f) Antidepressants, Others

- Trazodone (Desyrel, Desyrel Dividose, Oleptro)
- Mirtazapine (Remeron, Remeron SolTab)

Alzheimer Disease Medications

a) Cholinesterase Inhibitors

- Donepezil (Aricept, Aricept ODT)
- Rivastigmine (Exelon, Exelon Patch)
- Galantamine (Razadyne, Razadyne ER)

b) N-Methyl-D-Aspartate Antagonists

- Memantine (Namenda, Namenda XR)

c) Nutritional Supplement

- Capryl idene (Axona)

d) Combination Drugs

- Memantine/donepezil (Namzaric)

Cardiac Medications (including anti-hypertensive medications)

a) Anticoagulants

- Rivaroxaban (Xarelto)
- Dabigatran (Pradaxa)
- Apixaban (Eliquis)

- Heparin (various)
- Warfarin (Coumadin)

b) Antiplatelet Agents

- Aspirin
- Clopidogrel (Plavix®)
- Dipyridamole
- Prasugrel (Effient)
- Ticagrelor (Brillanta)

c) Angiotensin-Converting Enzyme (ACE) Inhibitors

- Benazepril (Lotensin)
- Captopril (Capoten)
- Enalapril (Vasotec)
- Fosinopri 1 (Monopri 1)
- Lisinopril (Prinivil, Zestril)
- Moex ipri 1 (Univasc)
- Perindopril (Aceon)
- Qu inapri 1 (Accupril)
- Ram ipri 1 (Altace)
- Trandolapri 1 (Mavik)

d) Angiotensin II Receptor Blockers (or Inhibitors)

- Candesartan (Atacand)
- Eprosartan (Teveten)
- Irbesartan (Avapro)
- Losartan (Cozaar)
- Telmisartan (Micardis)
- Valsartan (Diovan)

e) Angiotensin-Receptor Neprilysin Inhibitors (ARNIs)

- Sacubitril/valsartan (Entresto)

f) Beta Blockers

- Acebutolol (Sectral)
- Atenolol (Tenormin)
- Betaxolol (Kerlone)
- Bisoprolol/hydrochlorothiazide (Ziac)
- Bisoprolol (Zebeta)
- Metoprolol (Lopressor, Toprol XL) - Nadolol (Corgard)
- Propranolol (Inderal)
- Sotalol (Betapace)

g) Combined alpha and beta-blockers

- Generic name - carvedilol, Common brand names - Coreg
- Generic name - labetalol hydrochloride, Common brand names - Normodyne, Trandate

h) Calcium Channel Blockers

- Amlodipine (Norvasc, Lotrel)
- Diltiazem (Cardizem, Tiazac)
- Felodipine (Plendil)
- Nifedipine (Adalat, Procardia) - Nimodipine (Nimotop)
- Nisoldipine (Sular)
- Verapamil (Calan, Verelan)

i**) Digitalis Preparations** (Also known as Digoxin and Digitoxin)

- Lanoxin

j) Diuretics (Also known as Water Pills)

- Amiloride (Midamor)
- Bumetanide (Bumex)
- Chlorothiazide (Diuril)

- Chlorthalidone (Hygroton)
- Furosemide (Lasix)
- Hydro-chlorothiazide (Esidrix, Hydrodiuril)
- Indapamide (Lozol)
- Spironolactone (Aldactone)

k) Vasodilators

- Isosorbide dinitrate (Isordil)
- Nesiritide (Natrecor)
- Hydralazine (Apresoline)
- Nitrates
- Minoxidil

i) Antiarrhythmic Agents

Class I: Fast sodium (Na) channel blockers

- la - Quinidine, procainamide, disopyramide
- lb - Lidocaine, phenytoin, mexiletine
- lc - Flecainide, propafenone, moricizine

Class II: Beta blockers

- Propranolol Esmolol
- Timolol
- Metoprolol - Atenolol

Class III: Potassium (K) channel blockers

- Amiodarone
- Sotalol
- Ibutilide
- Dofetilide

Class IV: Slow calcium (Ca) channel blockers

- Verapami
- Diltiazem

Class V: Variable mechanism

- Adenosine
- Digoxin
- Magnesium sulfate

Respiratory Medications

1. Chronic Obstructive Pulmonary Disease (COPD) Medications

a) Beta2-Adrenergic Agonists, Short-Acting

- Albuterol (Proventil FIFA, Ventolin HFA, ProAir I IFA)
- Metaproterenol
- Levalbuterol (Xopenex, Xopenex HFA)

b) Beta2-Adrenergic Agonists, Long-Acting

- Salmeterol (Serevent Diskus)
- Formoterol (Perforomist)
- Arformoterol (Brovana)
- Indacaterol, inhaled (Arcapta Neohaler)
- Olodaterol inhaled (Striverdi Respimat)

c) Anticholinergics, Respiratory

- Ipratropium (Atrovent HFA)
- Tiotropium (Spiriva)
- Aclidinium (Tudorza Pressair)
- Umeclidinium bromide (Incruse Ellipta)
- Glycopyrrolate inhaled (Seebri Neohaler)

d) Xanthine Derivative

- Theophylline (Elixophyllin, Theo-24, Theochron)
- Aminophylline
- Methylxanthine

e) Selective phosphodiesterase-4 (PDE-4) inhibitors

- Roflumilast (Daliresp)

f) Corticosteroids, Inhalant

- Fluticasone inhaled (Flovent)
- Budesonide inhaled (Pulmicort, Pulmicort Flexhaler)

g) Corticosteroids, Oral

- Prednisone
- Methylprednisolonc (Solu-Medrol, Medrol, A-Methapred)

h) Beta-Adrenergic Agonist and Anticholinergic Agent Combinations

- Albuterol/ipratropium (Combivent Respimat)
- Umeclidinium bromide/vilanterol inhaled (Anoro Ellipta)
- Tiotropium/olodaterol inhaled (Stiolto Respimat)
- Indacaterol, inhaled/glycopyrrolate inhaled (Utibron Neohaler)
- Glycopyrrolate inhaled/formoterol (Bevespi Aerosphere)

i) Beta2-Adrenergic Agonist and Corticosteroid Combinations

- Budesonide/formoterol (Symbicort)
- Fluticasone and salmeterol (Advair Diskus)
- Vilanterol/fluticasone inhaled (Breo Ellipta)

j) Antibiotics

- Amoxicillin (Moxatag)
- Doxycycline (Doryx, Monodox, Doxy 100, Adoxa)
- Trimethoprim/sulfamethoxazole (Bactrim, Bactrim DS, Septra DS)
- Cefuroxime (Zinacef, Ceftin)
- Azithromycin (Zithromax, Zmax)
- Clarithromycin (Biaxin)

k) Smoking Cessation Therapies

- Nicotine transdermal system (Nicoderm CQ)
- Nicotine gum (Nicorette Gum)
- Bupropion (Zyban)
- Varencline (Chantix)

2. Asthma Medications

a) Beta2-adrenergic agonist agents

- Albuterol sulfate (Proventil HFA, Ventolin HFA, ProAir HFA)
- Pirbuterol acetate (Maxair Autohaler)
- Levalbuterol (Xopenex)

h) Anticholinergic Agents

- Tiotropium (Spiriva Respimat)
- Ipratropium (Atrovent)

c) Anticholinergic agent combinations

- Ipratropium and albuterol (Combivent, DuoNeb)

d) Corticosteroid, oral

- Prednisone (Deltasone, Orasone)
- Prednisolone (Pediapred, Prelone, Orapred)
- Methylprednisolone (Solu-Medrol)

e) Long-acting beta2 agonists

- Salmeterol (Serevent)

f) Beta2-Agonist/Corticosteroid Combinations

- Budesonide and formoterol (Symbicort)
- Fluticasone and salmeterol (Advair HFA, Advair Diskus)
- Mometasone and formoterol (Dulera)
- Vilanterol/fluticasone furoate inhaled (Breo Ellipta)

g) Methylxanthines

- Theophylline (Theo-24, Theochron, Uniphyl)

h) Mast cell stabilizers

- Cromolyn sodium (Intal)

i) Corticosteroid, Inhalant

- Ciclesonide (Alvesco)
- Beclomethasone (QVAR)
- Triamcinolone, Flunisolide (Nasalide)
- Fluticasone (Flovent Diskus, Flovent HFA)
- Budesonide (Pulmicort Flexhaler or Respules)
- Momestasone (Asmanex Twisthaler)

Triamcinolone inhaled (Aerospan HFA)

j) Leukotriene Receptor Antagonist

- Zafirlukast (Accolate)
- Montelukast (Singulair)
-

k) Monoclonal Antibodies, Anti-asthmatics

- Omalizumab (Xolair)
- Mepolizuman (Nucala)
- Reslizumab (Cinqair)

CHAPTER X

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