USING ELECTROENCEPHALOGRAPHY AND STRUCTURED DATA COLLECTION TECHNIQUES TO MEASURE PASSENGER EMOTIONAL RESPONSE IN HUMAN-AUTONOMOUS VEHICLE INTERACTIONS

by

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ABSTRACT

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Wide spread consumer adoption of self-driving cars (SDC) is predicated on a level of trust between humans and the autonomous vehicle. Despite advances being made in the technical abilities of SDCs, recent studies indicate that people are negatively predisposed toward utilizing autonomous vehicles. To bridge the gap between consumer skepticism and adoption of SDCs, research is needed to better understand the evolution of trust between humans and growing autonomous technologies. The question of mainstream acceptance and requisite trust is explored through integration of virtual reality SDC simulator, an electroencephalographic (EEG) recorder, and a new approach for real-time trust measurement between passengers and SDCs. An experiment on fifty human subjects was conducted where participants were exposed to scenarios designed to induce positive and negative trust responses. Emotional state was quantified by the EEG beta wave to alpha wave power ratio, and participants self-reported their levels of trust in the SDC after each segment.

I wholeheartedly dedicate this thesis to Dr. Nojoumian, my parents, and Caroline.

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CHAPTER 1
INTRODUCTION

Trust can be conceptualized as a belief that an entity will act with benevolence, integrity, predictability, or competence [8]. Recent studies indicate that people have negative attitudes toward utilizing autonomous platforms [9, 10]. With the growth and the increase in the complexity of autonomous systems in the 21st century, managing the trust of users in such systems has become an important concept when designing new autonomous systems. Numerous studies in the domain of trust and AI have suggested that the management and the constant improvement of this mutual trust between autonomous systems and their users will be one of the primary challenges the industry professionals will face when trying to popularize the use of fully autonomous systems [11, 12, 13]. These discoveries highlight the necessity and urgency of conducting research to better understand the evolution of trust between humans and growing autonomous technologies, and to provide technologies that are responsive to human trust.

In a 2018 study at Chapman University [14], a random sample of 1,190 adults from across the United States were asked their level of fear about ninety-four different phenomena. In regards to "Technology I don't understand" 17.8 percent reported feelings of fear. A 2018 multi-year tracking study from the American Automobile Association (AAA) indicated that 73 percent of American drivers report they would be too afraid to ride in a fully self-driving vehicle [15].

This research is timely and relevant given that the first pedestrian death from a self-driving car occurred this year [16]. Figure 1.1 shows data from the National Safety Council surveying public perception of SDCs before and after the first fatality

from a SDC.

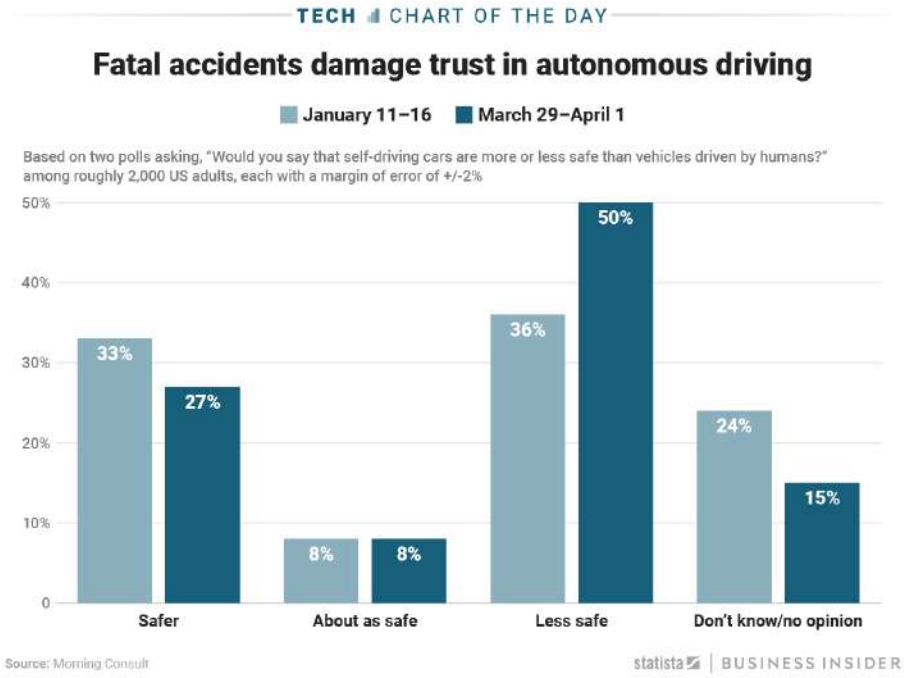


Figure 1.1: National Safety Council surveying public perception of SDCs before and after the first fatality from a SDC [1].

Google, Tesla, Mercedes-Benz, Ford, and others have created semi-autonomous cars, and they predict mass production of fully self-driving cars (SDCs) in the early 2020s [17]. The Boston Consulting group predicts autonomous cars will represents 25% of the global market by 2035. See figure 1.2. Widespread adoption of SDCs is dependent on consumers experiencing and maintaining positive emotional responses in SDCs. Electroencephalography (EEG) provides a non-invasive way to monitor brainwave activity, and a large body of research has focused on relating EEG responses to emotional states [18, 19, 20]. Recently, due to advances in dry electrode techniques and machine learning algorithms, there has been a proliferation of consumer grade and real-world applications of EEG for brain computer interfaces (BCI) [4]. EEGs are an appropriate choice to monitor SDC passenger response as they offer excellent temporal resolution [21].

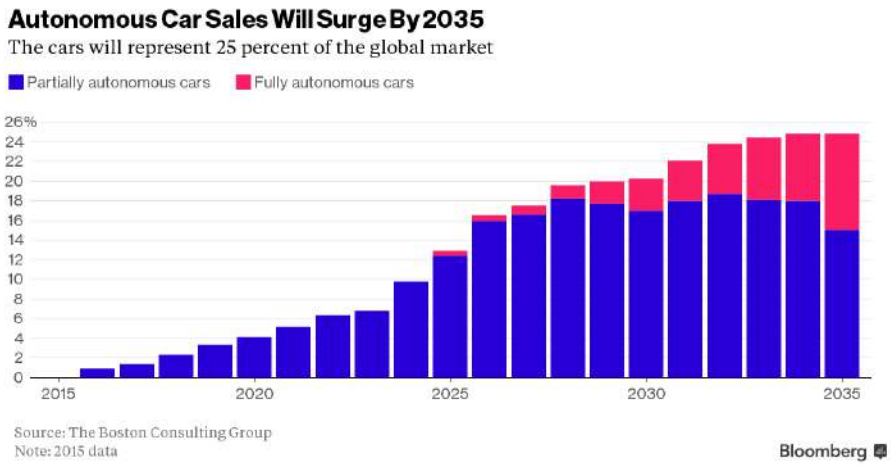


Figure 1.2: Boston Consulting Groups prediction of public adoption of SDCs [2].

In the experimental study the SDC passenger emotional responses is evaluated through EEG analysis of a passenger in a SDC simulator. The simulation is designed to elicit negative emotions in order to assess the level of passenger fear, stress and anxiety in response to autonomous control actions of the SDC. Ultimately, it is envisioned that such information can be used to develop and inform the SDC autonomous control of maneuvers that elicit negative emotional response in a passenger, and adjust its behavior accordingly.

1.1 NOVELTY OF OUR RESEARCH

The uniqueness of this research lies in the immersiveness of the SDC simulator. Previous research does not appear to have implemented a virtual reality (VR) headset along with a motion chair to create a SDC simulation while monitoring the EEG response of the passenger. This work builds on prior work from [22], [23] which showed that the simulator is highly effective for collecting real-time data from human subjects. The previous work only required subjects to self-report, while the implementation of an EEG brainwave monitor has potential to provide objective data. The combination of an immersive simulator, real time data collection coupled with EEG

monitoring provides unique insights. The primary objective is to classify participants emotional response while in positive and negative emotion inducing scenarios in the SDC simulator.

Other works have created models of trust between humans and autonomous systems. Hoff .et .al [24] performed a survey of trust between humans and autonomous systems, and built a three-layered trust model based on current research. The three layers of trust are dispositional trust, situational trust, and learned trust. Dispositional trust represents an individual's enduring tendency to trust automation. Situational trust depends on the specific context of an interaction. Learned trust is based on past experiences relevant to a specific automated system. The model presented in the current work uses a Sequential and Structured Data Collection approach to understand how the human mind goes from one specific trust-state to another one in a sequence of events.

1.2 HIGHLIGHTS OF OUR DISCOVERIES

The research revealed interesting insights into how different driving styles of SDCs effects the levels of trust between humans and autonomous vehicles, how different demographics groups and psychological predisposition effect trust with a SDC, and if EEG is an effective means to assess passenger emotional state inside of a SDC.

Below are some of the highlights of our findings (see chapter 5.4 for a full report of these findings).

1. The participants reported higher trust levels after experiencing trust building segments and reported lower levels of trust after trust reduction segments. This indicates the effectiveness of the SDC simulator as a safe platform to properly evaluate how passengers will react inside of a SDC.

2. Analysis of the demographic and survey questions indicates that demographic

background did not have a significant effect on how passengers rated their levels of trust with the SDC. Certain psychological questions on trust did correlate with how passengers reported their levels of trust in the SDC. Participants that indicated they are more trustful, did report higher levels of trust in the SDC after each segment, and participants that indicated they are less trustful, reported lower levels of trust in the SDC after each segment.

3. In a controlled experimental setting using the mean EEG beta/alpha wave band power as an indicator of feeling stress and anxious in a SDC appears to be effective when the stress inducing event is dramatic and strong within a small time interval, but becomes more difficult to obtain meaningful data when the incident does no elicit a very strong response or the time interval is long. It appears that EEG will be difficult to use in real world situations as the data easily becomes very noisy, even after appropriate preprocessing.

The thesis is organized as follows. Chapter 2 cover preliminary materials on Electroencephalographic and Virtual Reality. Chapter 3 reviews relevant literature and work in the field. Chapter 4 covers the design and setup of the fully immersive SDC simulator and goes over specifications of the Emotiv EPOC+ EEG used for brain wave signal acquisition. Chapter 5 covers the experimental design and results. Concluding remarks are made in Chapter 6.

CHAPTER 2

PRELIMINARY MATERIALS

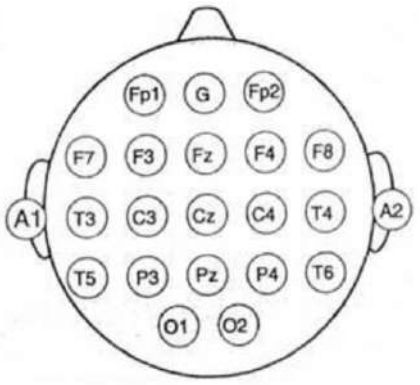
2.1 ELECTROENCEPHALOGRAPHIC

Electroencephalographic (EEG) is a noninvasive way to monitor electrical activity of the brain. EEG monitors the brain's electrical activity over time from multiple electrodes placed on the scalp.

Billions of neurons create the human brain's electrical charge. Neurons are electrically charged by membrane transport proteins that pump ions across their membranes. Ions of similar charge repel each other, and a chain reaction of ions pushing each other creates a wave. When the wave of ions reaches the electrodes on the scalp, they push or pull electrons on the metal in the electrodes. Since metal conducts the push and pull of electrons easily, the difference in push or pull voltages between any two electrodes can be measured by a voltmeter. EEG is the recording of theses voltages in the time domain. The electrical activity of a single neuron cannot be detected, so EEG reflects the summation of the synchronous activity of millions of spatially together neurons [25].

Electrodes are placed on subjects based on the 10-20 system which is standardized and internationally recognized methodology. In this system adjacent electrodes are either 10% or 20% of the total front-back or right-left distance on the subject head. Each electrode name represents an area of the brain. The nomenclature is F = frontal; Pf = Pre-frontal; C = central; P = parietal; T = temporal; O = occipital; A = auricular (ear); Fp = fronto-polar. Even numbered electrodes indicate the right side of the head, and odd numbers indicate an electrode is on the left side of the

brain. Midline electrodes are designated using "z". See Figure 2.1 for the electrode placement on a head in the 10-20 system [3].



Brain Area	Left	Midline	Right
Frontal Pole	Fp1	Fpz (G)	Fp2
Frontal	F3	Fz	F4
Inferior Frontal	F7		F8
Mid-Temporal	T3		T4
Posterior Temporal	T5		T6
Central	C3	Cz	C4
Parietal	P3	Pz	P4
Occipital	O1		O2

Figure 2.1: 10-20 Electrode Placement[3].

Analysis of brain waves from EEG typically look at event-related potentials (ERP) or the spectral content. ERP analyzes potential fluctuations related to timing of a specific event. Spectral analysis looks at the type of neural oscillations in the frequency domain. Other techniques involve averaging the EEG activity across a time window in relation to stimulus of the subject. Signal artifacts can be caused by excessive eye blinking, head movement, and bad electrode contact [26].

Compared to other brain imaging techniques like fMRI or PET scans, EEG is significantly less expensive, more tolerant to subject movement, and is much smaller and compact. EEG also has excellent temporal resolution. EEG does have low spatial resolution and low signal to noise ratio, requiring signal processing to glean meaningful results from the data [27].

An EEG signal represents the difference between the voltages of two electrodes. There are various was to represent these differences, covered below:

1. **Sequential montage:** Each channel represents the difference between two adjacent electrodes.

2. **Referential montage:** Each channel represents the difference between a cer-

tain electrode and a designated reference electrode that can be placed in any position.

3. **Average reference montage:** The outputs of all of the electrodes are averaged and used as the common reference for each channel.

4. **Laplacian montage:** Each channel represents the difference between an electrode and a weighted average of the surrounding electrodes.

Brain waves are typically characterized by varying frequency bands. Delta waves are below 4 Hz and indicate slow wave sleep. The Theta band exists between 4-7 Hz and is observed when subjects are drowsy. The Alpha band (8-14 Hz) is present during relaxed states. The Beta band (16-31 Hz) represents active thought, focus, and high alert. The Gamma band occurs in the (32-100 Hz) frequency bands [3], [28].

Wang et. al.[4] found that the features with the most information on emotional response were mainly on right occipital lobe and parietal lobe in alpha band, the parietal lobe and temporal lobe in beta band, left frontal lobe and right temporal lobe in gamma band. See Figure 2.2. It seems reasonable that these emotional response brainwaves do not appear to originate in the frontal cortex associated with higher thought processes and planning, but are closer to the occipital, brain stem, and limbic system where emotions are thought to be processed.

Jun & Smitha [29] found that effective stress is indicated by a decrease of EEG alpha band power and increase in beta band power. Conventionally, the alpha band contains frequencies from 8-14 Hz, the beta band 16-31 Hz [30]. Haak et. al. [21] also found that there is a strong positive correlation between eye blinking frequency and the emotional stress level of drivers. Additionally, Putman at al. [31] found that slow wave (SW) / fast wave (FW) ratio weakly correlates with with fear as well as anxiety. Ratios were calculated by dividing slow wave (theta 4-8 Hz, and delta 0.5-4Hz) power density by fast wave (beta) power density. Wang et al. [4] compared

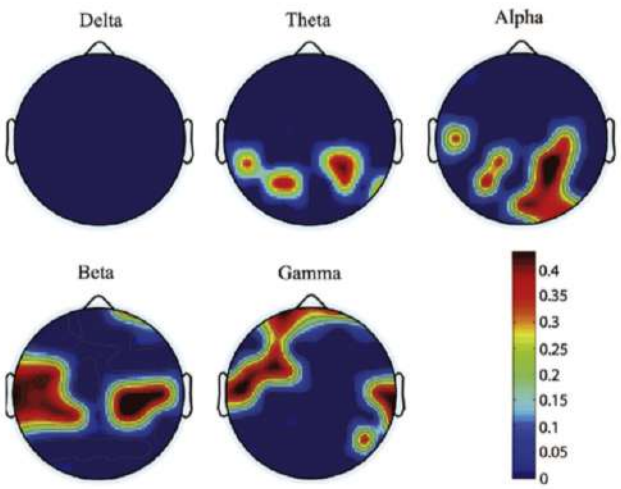


Figure 2.2: Distribution of the top 50 subject-independent features for emotional state from Wang et. al. [4].

several spectral decomposition methods, and found that the power spectrum is the most robust feature in analyzing EEG waves for emotion features.

2.2 VIRTUAL REALITY

Virtual Reality (VR) allows complete control of test subjects exposure to stimulus, and provides a safe test bed to expose subjects to situations that other wise may be dangerous. In VR simulations immersion is an objective description of the technical capabilities of the VR system that describes how close the sensations induced by virtual environment are to those of a real world environment. Factors that effect the level of immersion in a virtual environment include how much of the human visual field the simulation occupies, the stereoscopic aspects of the simulation, how accurate the surround/3D sound is, and the visual quality and fidelity of the simulation. Presence is the user's psychological response to the virtual environment. Different users can have varying levels of presence in a virtual environment that has the same objective level of immersion. Presence is effected by psychological and cognitive factors. Users that have higher levels of presence in a virtual reality will experience higher levels of

engagement with the virtual environment. Presence in a virtual reality can be assed through questionnaires, physiological response, and measures of participants behavior in the virtual environment [32], [33], [34].

In "A Framework for Immersive Virtual Environments" Slater .et .al [34] consider factors that can effect presence:

1. **Inclusive:** The virtual reality simulator should not allow the participants to receive sensory input from the physical world that is not meant to be part of the virtual environment.

2. **Vividness:** The more realistic the virtual reality environment looks, the higher level of presence users will experience. This includes the field of view and stereopsis of the virtual environment.

3. **Proprioceptive Matching:** Proprioceptive sense matching visual sense results in higher levels of presence.

4. **Extensiveness:** Sound in the virtual reality environment should be spatialized to create higher levels of presence.

5. **Plot:** When users interact with the virtual environment they experience higher levels of presence.

Slater .et .al [35] conducted an experiment on 16 participants to assess the effect of human movement on presence in a virtual reality environment. In one condition the participant "walks in place" to move through the virtual environment, and in the other condition the participant moves through the virtual environment based on the direction of their gaze. Participants in both conditions were tasked with taking an object to a chair in the virtual environment. The results found that subjective rating of presence in a virtual environment was significantly higher in the "walks in place" condition.

Augmenting a virtual environment with low-fidelity haptic objects significantly improves sense of presence in a virtual environment. Insko et. al. [36] found adding a 1.5 inch physical ledge to a visual cliff virtual environment increased participants sense of presence. Presence in the virtual environment was assessed through questionnaires, observed participant behaviors, and physiological responses. Participants experienced higher changes in heart rate, skin conductivity, and skin temperature when they were in the condition using the 1.5 inch physical ledge.

Strickland et. al. recorded 14 subjects brain waves using a standard commercial EEG, while they performed tasks in similar virtual and real environments. The participant's EEG data indicated that there exists a difference between how brains perform real and virtual image processing [37].

While virtual reality provides many benefits in the research domain it should be noted that VR sickness can occur. Symptoms include filling dizzy, nauseous, and headaches. It occurs when there is a discrepancy between perceived motion in the virtual environment, and the actual motion of the real environment. Another common trigger of VR sickness is when there is visual lag in the virtual environment [38].

CHAPTER 3

LITERATURE REVIEW

3.1 HUMAN TRUST WITH SELF-DRIVING CARS

While the idea of using fully self-driving cars is gaining acceptance, a majority of consumers still have fears and reservations about actual use. A 2018 report by the American Automobile Association (AAA) indicates that 63 percent of U.S. drivers report feelings of fear at the prospect of riding in a fully self-driving vehicle [39]. The baby boomer generation reported the highest rate of feeling afraid to ride in a fully self-driving vehicle at 68%, compared to Millennials at 49%.

A 2014 internet based survey of 347 Austinites conducted across various socio-demographics, by Bansal et. al. [40] found that 19% of respondents had no interest in owning a completely autonomous vehicle. The main issues participants cited for owning a fully SDC was that 50% of respondents were concerned about equipment or system failure and 48% were concerned about interactions with human operated vehicles. Only 7% of respondents indicated that learning to use a fully SDC was a concern.

The survey revealed passengers have varying levels of trust in SDCs predicated on the driving situation. 70% of respondents would ride in a SDC on a highway, while only 46% would use a SDC in city traffic. Personal adoption and acceptance of SDC is influenced by peers as 50% of respondents reported that personal SDC use depended on use by friends and neighbors. Acceptance of SDCs varies across demographics as high income, men, living in urban areas reported high levels of interest in using a SDC, while older drives reported significantly lower levels of interest in using a SDC.

Hulse et. al. [41] found that gender, age and risk taking tolerance have influence on perception of safety in a SDC. The work supported prior work, indicating that young men show the greatest willingness to accept SDCs. Hulse et. al. [41] considered not just the passenger interaction with a SDC, but also pedestrian interaction with a SDC. Passengers perceived SDCs as riskier than a human-operated car, while pedestrians perceived SDCs as less risky than a human-operated car.

Morris et. al [42] used a driving simulator to expose 28 participants to manual and automated driving simulation scenarios. Participants skin conductance and trapezius muscle tension was recorded while in the simulation to asses the participants stress levels. Participants also reported their subjective level of trust. The results indicated that participants had higher physiological indicators of stress while in the SDC simulation. The study also revealed that participants who subjectively reported low levels of trust in the SDC simulation exhibited higher physiological indicators of stress.

Objective performance is not the only factor that affects users perception of safety and trust in a SDC. Waytz et. al [43] ran 100 participants through a driving simulator that drove either a normal human operated car (Normal condition), a fully autonomous SDC (Agentic Condition), or an SDC with identical capabilities, except additional anthropomorphic features were added (Anthropomorphic Condition). The anthropomorphic SDC received a name, a gender, and a human voice through prerecorded audio files that were played during the simulation.

In each of the three simulation conditions the car is hit by another vehicle in an unavoidable accident. As expected participants in the Agentic and Anthropomorphic conditions blamed the car more for the accident than did those in the Normal condition, however more interesting was that participants blamed the vehicle significantly less in the Anthropomorphic condition than in the Agentic condition.

In the Anthropomorphic condition participants reported significantly higher levels of trust in the vehicle then those in the Agentic condition. These findings indicate a

meaningful benefit to humanizing autonomous systems to help spread acceptance of SDCs.

3.2 EEG IN SELF-DRIVING CARS

Regarding EEG applications to SDCs, Lin et. al. [44] found that the EEG responses of the alpha and gamma bands in the left and right motor cortex, parietal, lateral occipital, and occipital midline brain areas were highly correlated to subjective motion sickness levels. They created a driving simulator and implemented a neural fuzzy inference network to estimate a car passenger's sickness level based on EEG features while in the simulation. The overall performance of this model achieved a prediction accuracy of 82%.

Yeo et. al. [45] created a support vector machine (SVM) EEG classifier that could correctly identify if a driver was in drowsy state with 99.3% accuracy and was able to predict when drivers enter a drowsy state with a 90% accuracy. Dominant beta wave activity indicated that a driver was alert, while a decrease in the amplitude or frequency of the alpha rhythm indicated a drowsy state. Fast eye blinks were associated with alertness and slow eye blinks were associated with a drowsy state. The extracted features came from the power spectrum of each 10 second EEG epoch.

EEG can be applied as a form of systems control. Meng et. al. [46] found that subjects who wore a noninvasive EEG could modulate their brain activity to control a robotic arm to perform reach and grab tasks in three dimensional space with a high level of accuracy. Control in three dimensions was achieved by a two-step sequential experimental design with control of the robotic arm reduced in each step to a two dimensional plane. Brain wave activity was monitored in the motor cortex and participant imagination of movement in the left hand, right hand, both hand, and relaxation corresponded to the respective left, right, up, and down movement of the robotic arm.

Ghring et. al. [47] created a car controlled by the user's modulation of brain waves while wearing an EEG. In one protocol the car is completely controlled by the user's brain waves, but the precision of the vehicle control was not high enough to be used in real world scenarios. In the other protocol, the user is prompted to make choices (i.e. left or right turn) at certain decision points in the course, these results found a high level of precision.

Hu et. al. [48], [49] built a trust sensor model that uses psychopathological response from EEG and galvanic skin response (GSR - perspiration sensor) devices that achieves 71% accuracy in assessing trust levels. This metric was evaluated through experimental trials with human subjects who reported how they would feel in certain situations in a self driving car. EEG signal was sampled at 256 Hz and was recorded from 9 scalp sites (Fz, Cz, POz, F3, F4, C3, C4, P3, and P4 based on the 10-20 system). Both frequency and time domain features were taken from each trial. Response time of the participants in each trial was one of the main input variables to sense trust level in the time domain. In the frequency domain, the main input was high-beta band measurements from the right hemisphere and the parietal lobe (C4, P4, POz) that responded strongly to the discrepancy between trusting and distrusting situations. To achieve the 71% accuracy level, the study removed participants data that had low signal to noise ratios. Across demographic groups significantly different trust behavior was observed between US vs India and female vs male participants.

CHAPTER 4

SELF-DRIVING CAR SIMULATOR SETUP AND SPECIFICATIONS

The SDC Simulator is a safe platform to expose participants to a variety of driving scenarios. It is based on fusion of an Oculus Rift headset with an Atomic A3 Full Motion Simulator and offers a combination of complete visual, audio, and motion immersion that creates a convincingly realistic simulation. This platform allows for participants to safely be exposed to unique driving situations that would other wise offer potential risk to passengers if performed with real vehicles. This chapter covers the specifications and implementation of the SDC simulator. Figure 4.1 shows a participant in the simulator. See figure 4.2 for the participants view inside the simulator.



Figure 4.1: Participant using the SDC simulator.



Figure 4.2: View from the simulation. Each frame represents the participant's view as they turn their head to look around, illustrating the 360 degree view inside the simulator.

4.1 HARDWARE

4.1.1 Atomic A3 Motion Chair

The Atomic A3 Full Motion Simulator can move up to 71 degrees per second across a full 27 degree dual-axis movement range [50]. The Atomic A3 Simulator receives telemetry data for motion via UDP packets. Each UDP packet contains pitch values for front and back movements and roll values for left and right movements. The Atomic A3 Motion simulator has been used previously by NASA to create realistic moon rover simulations [51].

4.1.2 Oculus Rift Virtual Reality Headset

The Oculus Rift head set outputs 1080x1200 resolution per eye, at a 90 Hz refresh rate, a 110 degree field of view, and has headphones which output a 3D audio effect [52]. While wearing the Oculus Rift VR headset the participant can freely move their head 360 degrees to see the complete scene. Oculus Rift earbuds were used to fit

with the EPOC+ EEG so that the participant could wear both the Oculus and the EPOC+ simultaneously.

4.1.3 GoPro Fusion Camera

Driving situations were recorded using the GoPro Fusion Camera and edited using the GoPro Fusion Studio to produce 360 degree video. The videos were exported from Fusion Studio at 4k resolution as MP4s along with 360 degree MP3 audio files. The GoPro Fusion was mounted in a car to align with the drivers perspective. Different scenarios were enacted and recorded in a safe environment, and then used as footage for the SDC simulator.

4.1.4 Alienware Area 51

To play 360 degree 4K resolution videos in each lens of the Oculus Rift requires a machine with powerful processing. To meet these demands the application is executed on an AlienWare Area-51 Desktop equipped with an Intel Core i7-5960X processor along with dual NVIDIA GeForce GTX Titan Z graphics cards that achieves clock speeds greater than 4 GHz. This high performance machine allows for the dual 360 degree 4k videos to be played smoothly and seamlessly.

4.1.5 Emotiv EPOC+ EEG

The Emotiv EPOC+ was used for EEG signal acquisition, see figure 4.3. The EPOC+ records signals from 14 channels (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4) using a Sequential sampling montage. The sensor material are saline soaked felt pads. Two electrodes are used as references (CMS/DRL), the P3/P4 locations [5]. The 10-20 methodology of electrode application was used [53]. See Figure 4.4 for electrode placement. The signal was sampled at 128 Hz [5], providing 64 Hz total bandwidth per the Nyquist criterion [54].



Figure 4.3: EPOC+ EEG used for signal acquisition [5].

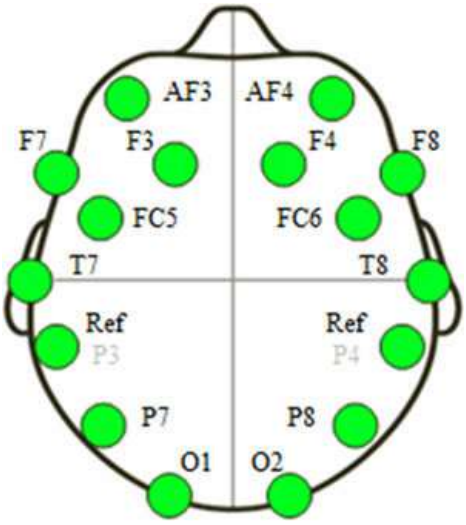


Figure 4.4: Emotiv EPOC+ EEG electrode placement [6].

Based on the previously discussed research [29, 31, 4] the ratio of the average power between the beta and alpha waves was used as the main feature to determine emotional state. A high beta/alpha power ratio indicates negative emotional response. A low beta/alpha ratio indicates positive emotional response. The average power in the delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), and beta (12-30 Hz) is computed from the PSD of the raw EEG data.

Since Wang et. al.[4] found that the features with the most information on emotional response were mainly on right occipital lobe and parietal lobe in alpha band, the parietal lobe and temporal lobe in beta band, the P7, T7 and O1 electrodes were the channels used for the signal processing and data analysis. In future phases of the research, more channels and interaction between channels will be analyzed.

Emotiv PRO software was used to monitor and save the participants brainwaves during the experiment, and Python was used for the signal processing of the data.

4.2 SOFTWARE

4.2.1 Unity Game Engine

The SDC simulator software application was built in the Unity Game Engine using C#. The Unity Game Engine is used primarily for video game development and has full integration with the Oculus Rift Head set to create virtual reality interfaces [55]. The SDC simulator software application synchronously sends the 360 degree video and audio to the Oculus Rift, and sends the telemetry motion data to the Atomic A3 Motion Chair. The Unity Game Engine was also used to build the gaze and select user input method used in the SDC simulator software application so that users can provide their response while in the SDC simulation. Finally the SDC software application also creates structured directories with files documenting the users responses and meta information.

4.2.2 Simtools

SimTools motion simulator software was used to send the telemetry data to the Atomic A3 motion simulator chair. The Video Ride Creator plugin was used to generate the telemetry points for each video in the simulation. The Video Ride Player plugin was used to send the telemetry points as UDP packets to Atomic A3's motion simulator Software, Symphinity, which received the UDP packets and moves the chair [56].

CHAPTER 5
RESEARCH METHODOLOGY

5.1 SEQUENTIAL AND STRUCTURED DATA COLLECTION APPROACH

The exposure of participants to the various segments builds on prior work from [7] and [23]. Segments are categorized into five distinct groups (See below).

1. **Initial Trust:** Segments that capture the initial trust of the passengers in the first few minutes of the interaction.

2. **Trust Escalation:** Segments were the subject's trust is increased. Involves smooth and predictable driving by the SDC without any complications.

3. **Trust Reduction:** Segments were human subject's trust is decreased. Involves the SDC driving eradictly and aggressively.

4. **Trust Mutation:** A sequence of mild incidents (e.g., a rapid lane change by the SDC) followed by critical incidents (e.g., stop-sign violation or near collision with another vehicle) and vice versa, can be negative or positive incidents.

5. **Re-Building Trust:** Segments designed to rebuild trust between the passenger and the SDC. Involves the SDC driving predictably and calmly after trust-damaging incidents.

The sample templates for five consecutive segments in a 10-minute scenario, are shown in Figure 5.1. These structured templates again build on prior work from [7]

Template-1	Template-2	Template-3	Template-4	Template-5	Template-6	Template-7	Template-8
Initial Trust	Initial Trust	Initial Trust	Initial Trust	Initial Trust	Initial Trust	Initial Trust	Initial Trust
Trust Reduction	Trust Reduction	Trust Escalation	Trust Escalation	Trust Escalation	Trust Escalation	Trust Reduction	Trust Reduction
Further Trust Reduction	Further Trust Reduction	Further Trust Escalation	Further Trust Escalation	Trust Reduction	Trust Reduction	Trust Escalation	Trust Escalation
Trust Mutation (negative)	Trust Mutation (positive)	Trust Mutation (positive)	Trust Mutation (negative)	Trust Mutation (positive)	Trust Mutation (negative)	Trust Mutation (positive)	Trust Mutation (negative)
Rebuild Trust	Rebuild Trust	Strengthen Trust	Rebuild Trust	Rebuild Trust	Rebuild Trust	Rebuild Trust	Rebuild Trust

Figure 5.1: Structured and Sequential Data Collection: Eight templates for various scenarios [7].

and [23] that illustrated this model as an effective method of real time trust evaluation with human subjects. Two out of eight structured templates were used in the present work (Templates 1 & 6).

5.2 EXPERIMENTAL DESIGN

Prior to the simulation, participants were asked to answer 17 demographic and psychological questions by filling out an anonymous survey. This survey is detailed in section 5.4.1. Participants were randomly placed in one of two possible SDC simulation scenarios that were based on Template 1 and Template 6 (Figure 5.1). Each scenario is made up of 5 segments. Specific scenario-segment pairs are denoted with a two letter abbreviation followed by the scenario and segment numbers, for example TR_{I-II} denotes trust reduction segment 2 of scenario 1. See tables 5.1 and 5.2.

Once the participant is in the SDC simulator, the EPOC+ EEG is attached to the participant. An initial 1 minute baseline is taken of the participant's brainwaves with no visual, audio, or motion stimulus. After the baseline, the scenario begins, and the EEG records the participants brainwaves for each segment.

Each segment is an exposure to an approximately 2 minute SDC driving simula-

tion. After each segment, the participant is presented with a Likert Scale that appears inside the Oculus Rift. The participant selects their response by focusing their gaze on the desired answer for five seconds while wearing the Oculus Rift. Figure 5.2 shows a sample question in the virtual reality space.

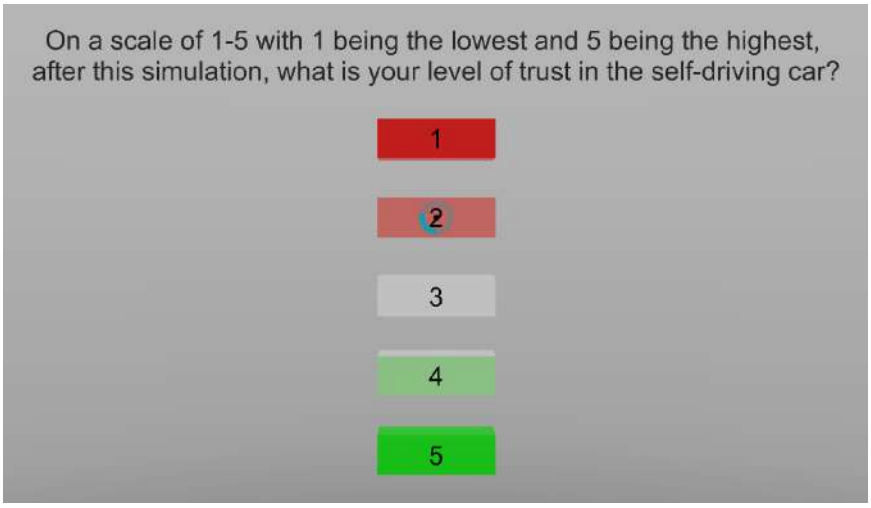


Figure 5.2: Virtual reality gaze input for user response.

During the response interval the participant responds to the question "On a scale of 1-5 with 1 being the lowest and 5 being the highest, after this simulation, what is your level of trust in the self-driving car?". After the participant responds, the application moves on to the next segment until the simulation scenario is complete. Tables 5.1 and 5.2 define the scenario and segment pairings.

An initial trust/trust escalation segment involved the SDC moving slowly and predictably while adhering to the rules of the road. A trust reduction segment involved the SDC along with Human-Driving Cars (HDC) moving erratically and unpredictably, breaking rules of the road including speeding, tailgating, and sudden lane changes. In the NM_{I-IV} segment, the SDC ran through a non-visible stop sign and nearly collided with another car and then proceeded to drive through a residential neighborhood. In the NM_{II-IV} segment, the SDC ran through a stop sign unexpectedly and detected a pedestrian and a bicyclist crossing a crosswalk and abruptly came

Table 5.1: Simulation Scenario 1 from Template 1

IT_{I-I}	Initial Trust
TR_{I-II}	Trust Reduction
TR_{I-III}	Further Trust Reduction
NM_{I-IV}	Negative Trust Mutation
RT_{I-V}	Rebuild Trust

Table 5.2: Simulation Scenario 2 from Template 6

IT_{II-I}	Initial Trust
TE_{II-II}	Trust Escalation
TR_{II-III}	Trust Reduction
NM_{II-IV}	Negative Trust Mutation
RT_{II-V}	Rebuild Trust

to a stop. A rebuild trust segment involved the SDC driving defensively and adhering to rules of the road. Note that HDCs were involved in all scenarios.

It is predicted that after the initial trust/trust escalation segments, the participants will respond with high levels of trust in the SDC, and after trust reduction segments, the participant will respond with low levels of trust in the SDC. It is also predicted that after the negative trust mutation segment, the participant will report a drastic decrease in trust.

For EEG response it is predicted that when trust damaging events occur in the simulation a high beta/alpha ratio will be observed in participants, indicating negative emotional response, and loss of trust. In trust building segments it is expected that low beta/alpha ratio will be observed in participants, indicating positive emotional response, calmness, and trust in the SDC simulator. It is also expected that spikes in the power of the beta/alpha ratio will correlate in time to when negative incidents occur inside the SDC simulator, e.g. in segment NM_{I-IV} when the SDC does not stop at an intersection and is nearly in a devastating car accident.

5.3 EEG SIGNAL PROCESSING

Based on the prior work discussed in Chapter 2.1 the P7, T7 and O1 electrodes were the channels used for the signal processing and data analysis. The channel that had the strongest connection for the specific participant was the channel used. It is expected that a high beta/alpha power ratio will be observed in negative emotional response scenarios and a low beta/alpha ratio will be observed in negative emotional response scenarios.

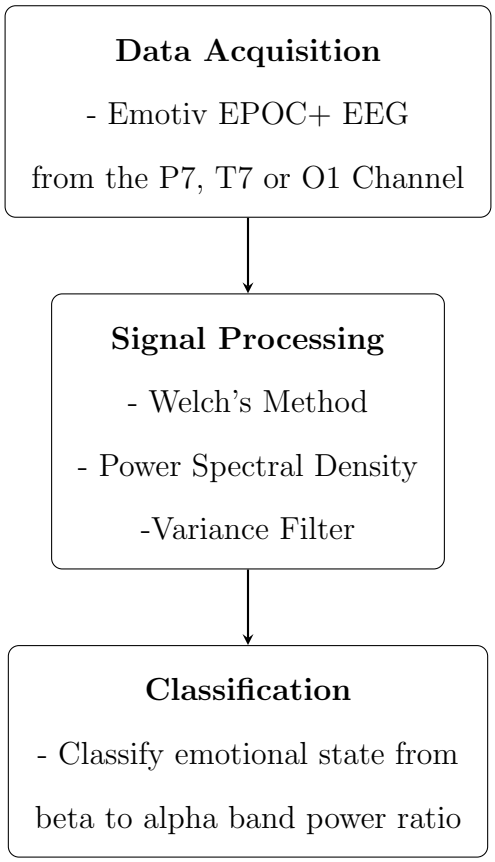


Figure 5.3: Workflow of EEG data analysis

The power spectral density of raw EEG data sampled at 128 Hz was computed in 4 second blocks using Welch's method with a 50% overlap. The beta to alpha power ratio was computed for each 4 second block by taking the ratio of the mean power in the respective frequency band. A low pass and high pass variance filter was applied

to reduce signal noise from participant head movement. Figure 5.3 represents the pipeline used to classify emotional state from the EEG data. Python was used for all data analysis. The signal processing of the EEG data is discussed more in depth in section 5.4.4

5.4 EXPERIMENT AND TECHNICAL RESULTS

Fifty subjects were recruited to participate in the 11 minute VR autonomous driving simulation. Participants were each given $25 Amazon gift cards for participating in the study [1]. At the beginning of each experiment, the participant was randomly placed in either Scenario 1 or Scenario 2. Participants were primarily recruited from the Florida Atlantic University campus.

5.4.1 Demographics & Psychological Questions

All fifty participants responded to 17 demographic and psychological assessment questions. Figures 5.4, 5.5 and 5.6 provide the questions and a breakdown of participant's responses.

[1] IRBNET ID #: 1187756-1

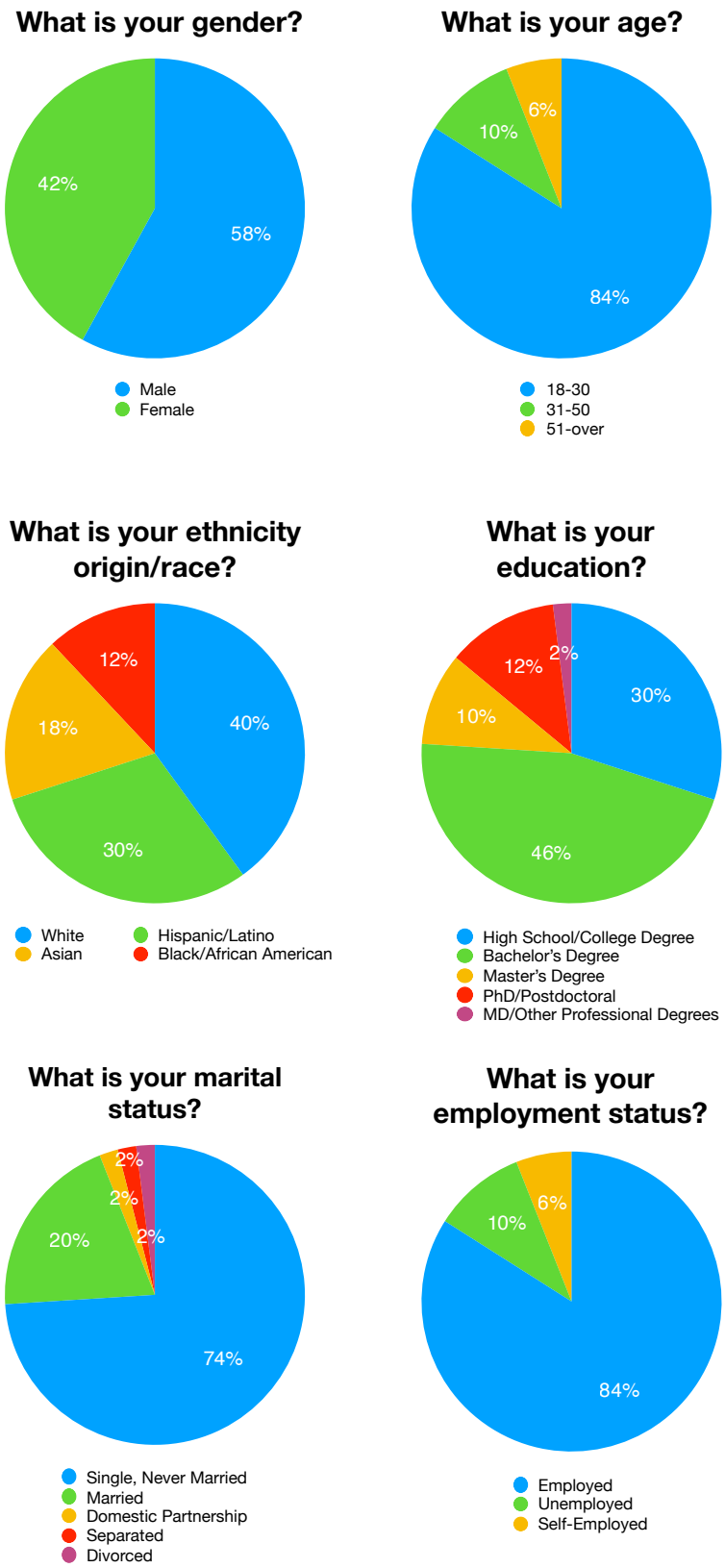


Figure 5.4: Participant's responses to demographic questions 1 - 6.

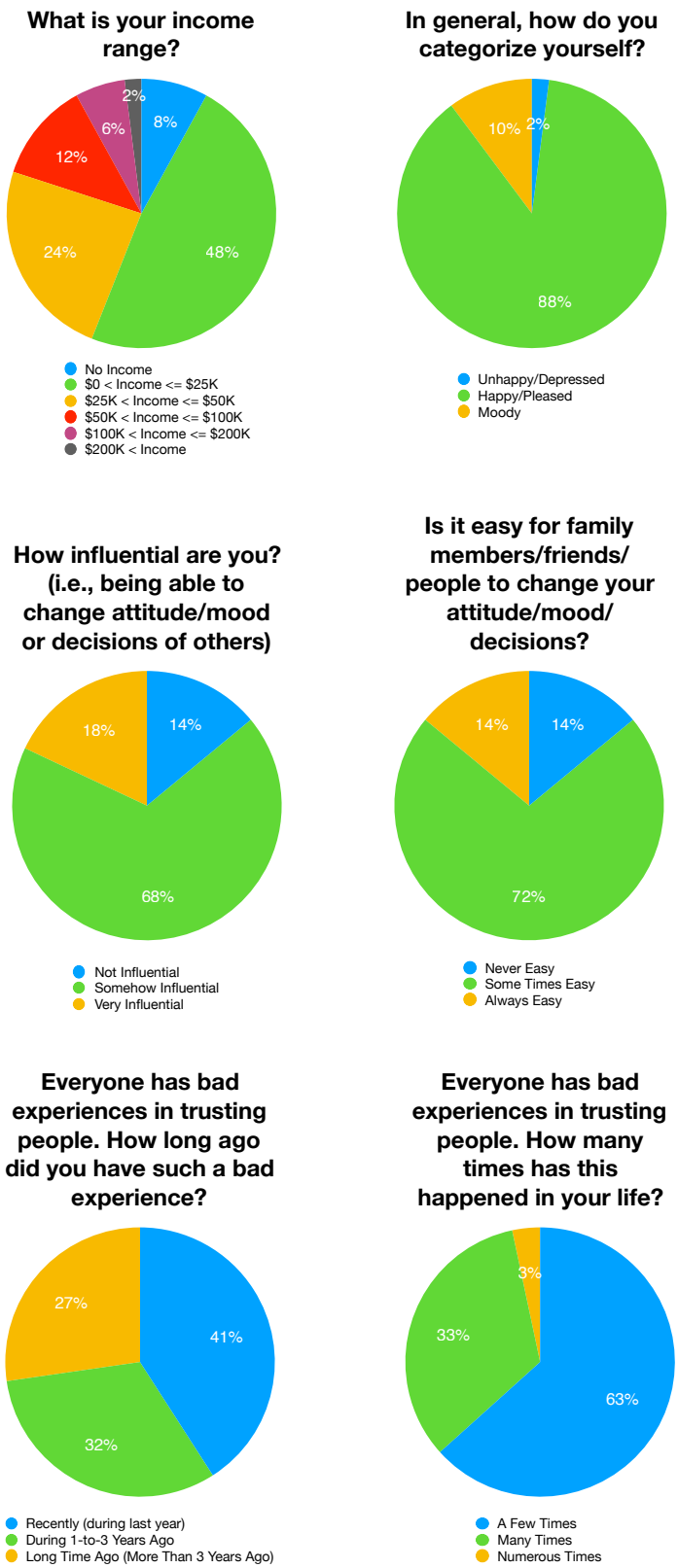


Figure 5.5: Participant's responses to demographic questions 7 - 12.

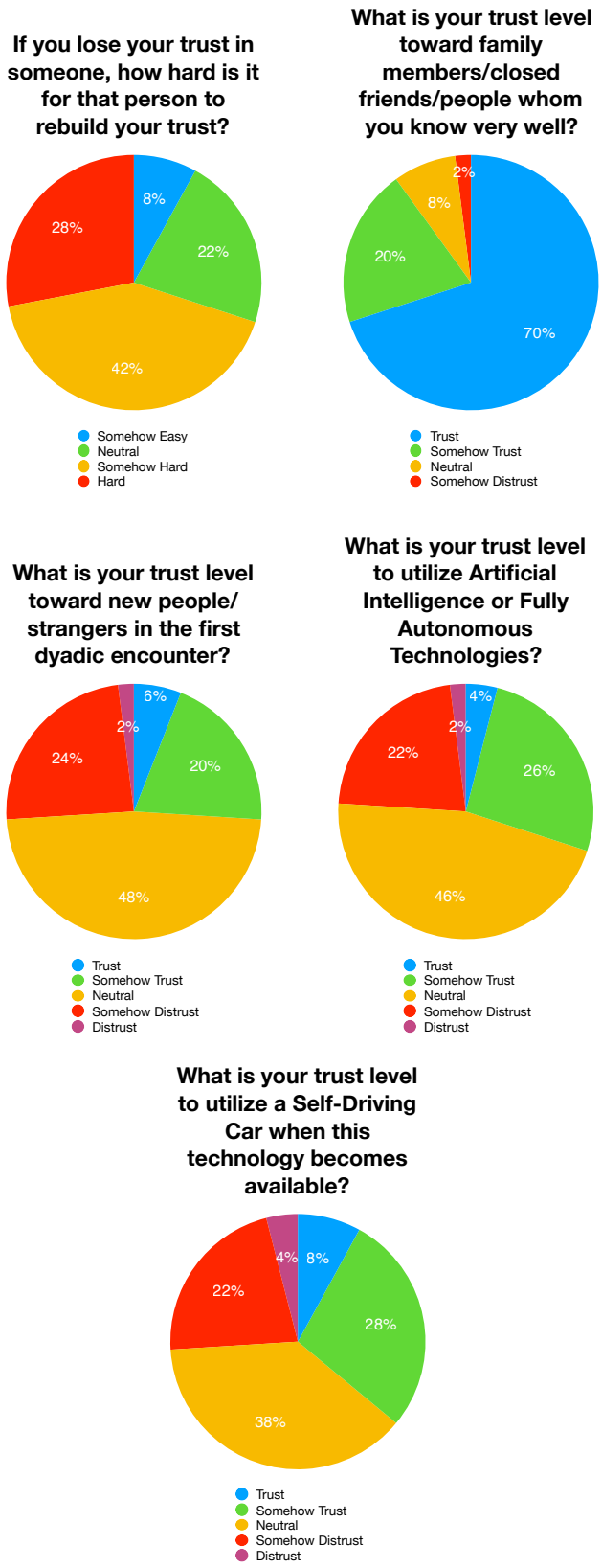


Figure 5.6: Participant's responses to demographic questions 13 - 17.

The Wilcoxon Rank Sum Test was performed across demographic and psychological assessment questions to determine if there was a significant difference between the populations of Scenario 1 and Scenario 2. Answers to the demographic and psychological assessment questions are not distinguishably different at the 0.05 p-value except for the question "What is your trust level toward family members/closed friends/people whom you know very well?" which had a p-value of 0.032. Figure 5.7 shows the difference in answers between the two Scenarios for this questions. This is the only demographic or psychological question that showed a significant difference between the two Scenario populations, otherwise there is no significant difference between the two populations. This difference indicates that the Scenario 2 group seems to be inherently less trusting than the Scenario 1 group.

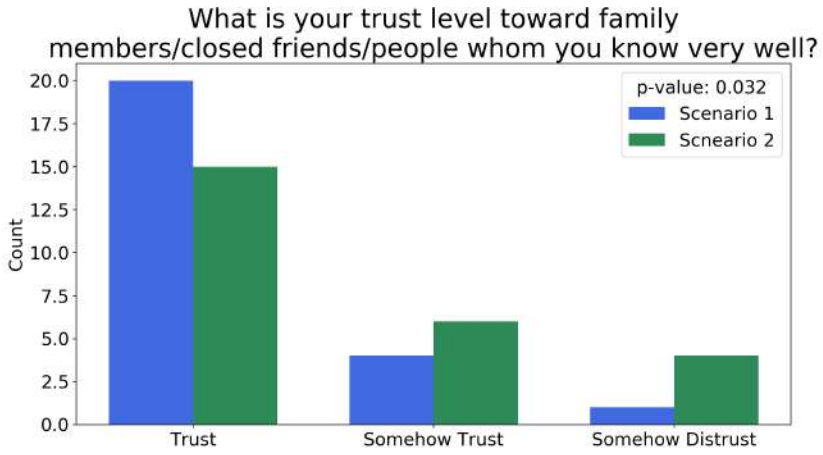


Figure 5.7: Compares answers to the only significantly different question responses between participants of Scenario 1 and Scenario 2.

5.4.2 Participant's Response

Scenario 1

Figure 5.8 shows participants response to "On a scale of 1-5 with 1 being the lowest and 5 being the highest, after this simulation, what is your level of trust in the self-

driving car?" after each segment in Scenario 1. The green box shows the quartiles of the dataset. The yellow whiskers extend to show the full distribution, except for points that are determined to be outliers using a method that is a function of the inter-quartile range. Pink lines are the median response.

In the initial trust segment (IT_{I-I}), participants responded with a mean score of 4.68±0.47, followed by a mean score of 3.72±0.96 in the first trust reduction segment (TR_{I-II}). After exposure to the further trust reduction segment (TR_{I-III}), the score decreased slightly to 3.68±1.25, followed by a large decline to 1.92 ±0.84 when exposed to the negative trust mutation segment (NM_{I-IV}). Finally, trust levels increased to 3.96±0.92 in the rebuild trust segment (RT_{I-V}). The largest change across segments was between the negative trust mutation (NM_{I-IV}) and the initial trust segment (IT_{I-I}), consistent with the expectation that erratic driving has the potential to severely reduce trust.

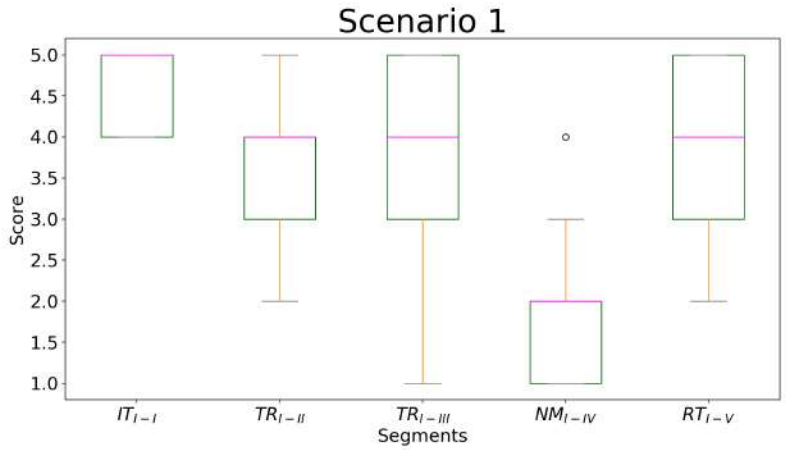


Figure 5.8: Scenario 1 participants reported trust level in the SDC.

To assess whether the observed scores are statistically different, the Wilcoxon Rank Sum Test was performed across segments; the resulting p-values are shown in Figure 5.9. Score changes in trust are not distinguishable above the 0.05 p-value between TR_{I-II} and TR_{I-III}, RT_{I-II} and TR_{I-V}, and RT_{I-III} and TR_{I-V}. All other comparisons show statistically significant changes in trust.

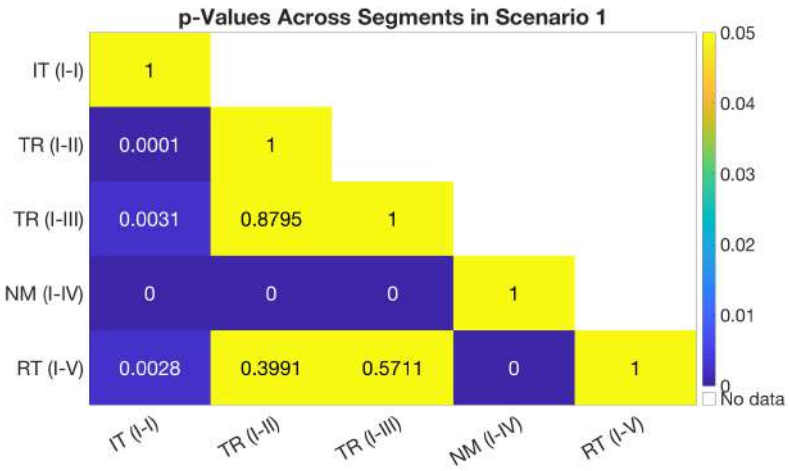


Figure 5.9: Wilcoxon Rank Sum Test: p-Values across segments in Scenario 1.

Scenario 1 performed as expected. Participants scored the initial trust and rebuild trust segments with high levels of trust. Participants scored the trust reduction segments with lower levels of trust, and the negative trust mutation segment with the lowest level of trust. As expected, the negative trust mutation had the lowest trust levels and was significantly lower than all other segments. This indicates the simulations effectiveness in reducing participants trust.

An interesting result is the difference between the initial trust segment and the final segment designed to rebuild trust. While participants scored their level of trust after RT_{I-V} at 3.96±0.92, a high value, it is significantly lower than the initial trust value (4.68±0.47), representing a 15% decrease. This seems to indicate that participants trusted the SDC less after being exposed to trust-damaging segments.

Scenario 2

Figure 5.10 shows participants response to "On a scale of 1-5 with 1 being the lowest and 5 being the highest, after this simulation, what is your level of trust in the self-driving car?" after each segment in Scenario 2. The green box shows the quartiles of the dataset. The yellow whiskers extend to show the rest of the distribution, except for points that are determined to be outliers using a method that is a function of the

inter-quartile range. Pink lines are the median response.

In the initial trust segment (IT_{II-I}), participants responded with a mean score of 4.40±0.69, followed by a mean score of 4.64±0.68 in the first trust escalation segment (TE_{II-II}). After exposure to trust reduction (TR_{II-III}), the score decreased to 3.68±1.12, followed by a further decline to 3.64 ±1.13 when exposed to the negative trust mutation (NM_{II-IV}). Finally, trust levels increased to 4.04±1.11 in the Rebuild Trust segment (RT_{II-V}).

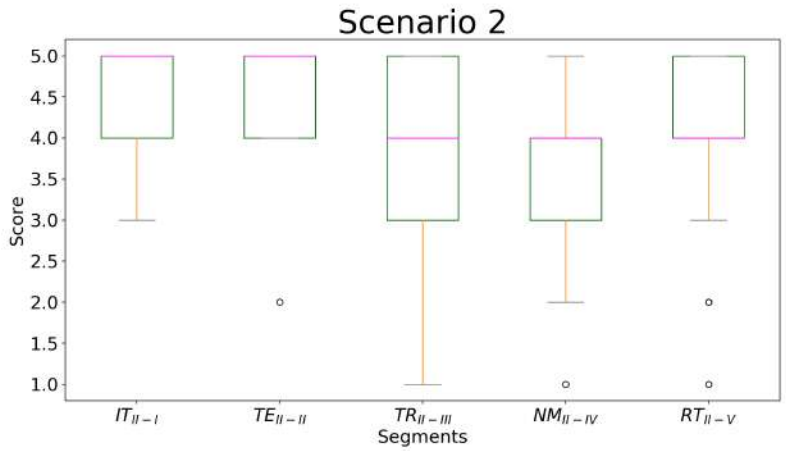


Figure 5.10: Scenario 2 participants reported trust level in the SDC.

Figure 5.11 shows the results of the Wilcoxon Rank Sum Test across segments in Scenario 2. Here, we see that scored changes in trust are not distinguishable above the 0.05 p-value between TE_{II-I} and IT_{II-II}, RT_{II-I} and IT_{II-V}, NM_{II-III} and TR_{II-IV}, RT_{II-III} and TR_{II-V}, and RT_{II-IV} and NM_{II-V}. All other inter-comparisons show statistically significant changes in trust.

In (NM_{II-IV}), the SDC approaches a crosswalk and stops for a pedestrian to cross the street. This was the only segment that involved the SDC interacting near a pedestrian. Participants reported low levels of trust after this segment and commented that they especially did not trust the SDC near pedestrians.

In Scenario 2, while participants score their level of trust after RT_{II-V} at 4.04 ±1.11, a high value, it is significantly lower than the initial trust segment (4.40

±0.69), representing a 8% decrease. This seems to indicate that participants trusted the SDC less after being exposed to trust-damaging segments.

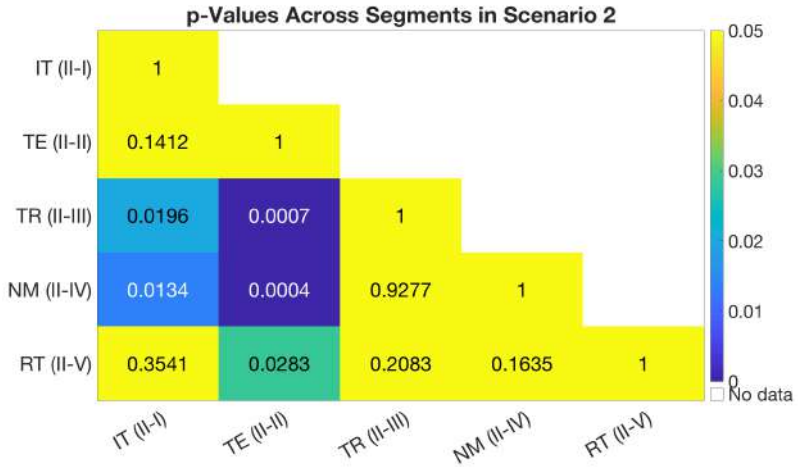


Figure 5.11: Wilcoxon Rank Sum Test: p-Values across segments in Scenario 2.

Scenario 1 vs Scenario 2

Figure 5.12 shows the results of the Wilcoxon Rank Sum Test across segments between Scenario 1 and Scenario 2. Segment (NM_{I-IV}) had the most significant difference in participant's rating of trust from all other segments. This is most likely because segment (NM_{I-IV}) was the most drastic portrayal of a malfunction in a SDC. In segment (NM_{I-IV}) the SDC runs through a stop sign, and comes within inches of colliding with another vehicle. The view from the participant's perspective of this incident can be seen in Figure 5.13.

The results of the experiment were generally consistent with our expectations. The participants reported higher trust levels after experiencing initial trust and trust escalation segments and reported distrust after the trust reduction segments, as well as high distrust after the negative trust mutation segment. Participants did not trust the SDC around pedestrians. Finally, participants in both groups were able to relatively rebuild their trust after the trust damaging Negative Trust Mutation segments.

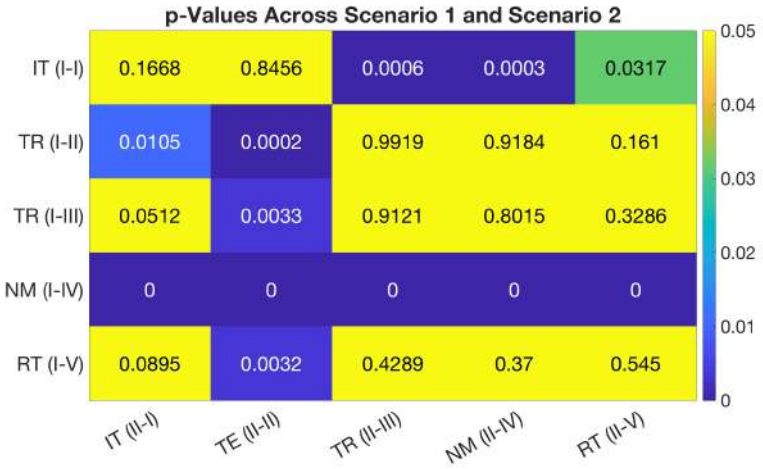


Figure 5.12: Wilcoxon Rank Sum Test: p-Values across segments in Scenario 1 & 2.



Figure 5.13: During the (NM_{I-IV}) segment an incident occurs were the SDC does not stop at an intersection and nearly collides with another vehicle. The frames from top to bottom show the progression of the incident from the perspective of the participant.

5.4.3 Demographics & Psychological Questions in Relation to Reported Trust Values

There was no significant difference in how members of different demographic groups (i.e. gender, age, ethnicity, education, marital status, employment status, and income range) reported their level of trust in the SDC after each segment or between Scenario 1 and Scenario 2.

There was a correlation in how participants responded to the psychological questions in the initial survey and how they reported trust values after each segment in the SDC. Participants that indicated once they lose trust in some one, it is difficult for them to rebuild that trust reported on average lower levels of trust in the SDC in both Scenario 1 and Scenario 2. These participants also did not rebuild their trust as quickly as other participants after exposure to the negative trust mutation segment.

Figures 5.14 and 5.15 show a comparison of the mean trust scores across segments between participants that responded to "If you lose your trust in someone, how hard is it for that person to rebuild your trust?" with "Neutral" and "Somehow Hard" for Scenario 1 and Scenario 2. These were the two most popular response from participants to this psychological question.

There was a correlation in how participants reported trust levels with artificial intelligence or fully autonomous technologies and how they reported trust values after each segment in the SDC. Participants that reported low levels of trust in artificial intelligence or fully autonomous technologies also reported on average lower levels of trust in the SDC in both Scenario 1 and Scenario 2.

Figures 5.16 and 5.17 show a comparison of the mean trust scores across segments between participants that responded to "What is your trust level to utilize Artificial Intelligence or Fully Autonomous Technologies?" with "Somehow Trust" and "Somehow Distrust" for Scenario 1 and Scenario 2. These were the two most popular response from participants to this psychological question.

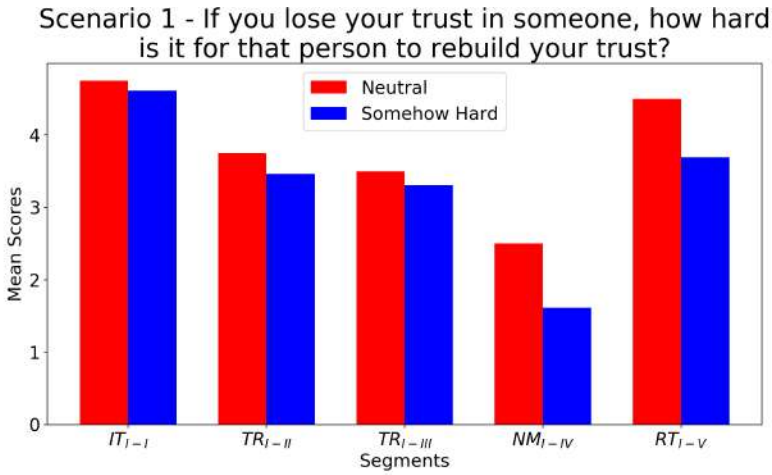


Figure 5.14: Scenario 1 average trust scores across segments separated by response to psychological question on interpersonal trust.

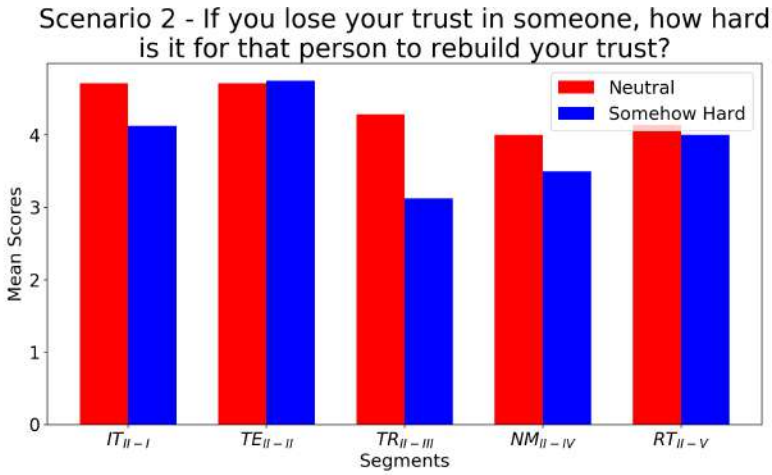


Figure 5.15: Scenario 2 average trust scores across segments separated by response to psychological question on interpersonal trust.

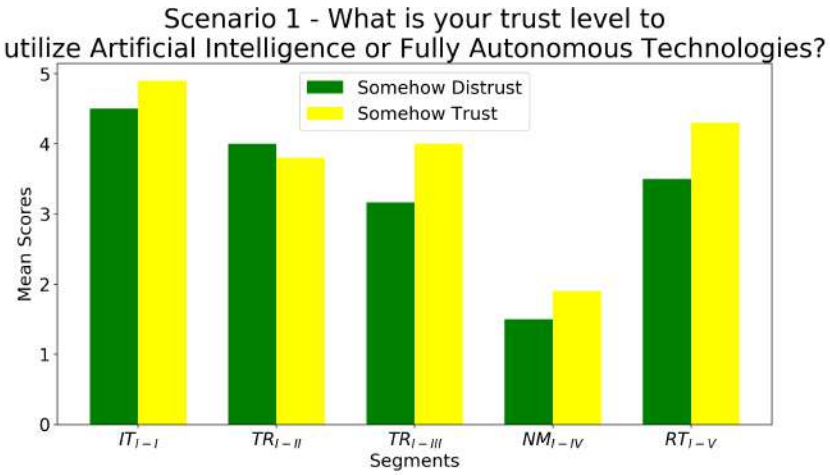


Figure 5.16: Scenario 1 average trust scores across segments separated by response to psychological question on trust in autonomous systems.

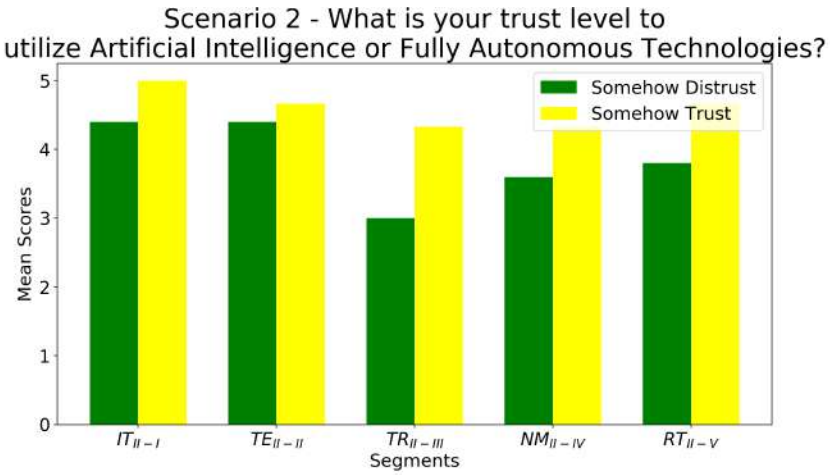


Figure 5.17: Scenario 2 average trust scores across segments separated by response to psychological question on trust in autonomous systems.

5.4.4 EEG Response and Data Cleaning

Per previous research discussed in Chapter 2.1 an increase in the beta/alpha power ratio in the parietal lobe indicates an increase in stress and anxiety. Participant 17 had a shaved head, and without the interference of hair between the scalp and the EEG electrode, a very strong and clear EEG signal was recored. Segment NM_{I-IV} and RT_{I-V} are compared since participants self-reported the largest difference in their trust levels (1.92 $\pm$0.84 and 3.96 $\pm$0.91 respectively) between these two segments, and as discussed in section 5.13, segment NM_{I-IV} contains the most stress inducing incident.

The top plot in figure 5.18 shows the beta/alpha power ratio across time of Participant 17 in segment NM_{I-IV} and RT_{I-V}. This plot shows that the mean beta/alpha power ratio in the NM_{I-IV} segment of 5.6 dB was higher than the mean beta/alpha power ratio of 2.9 dB in the RT_{I-V} segment, indicating that the participant had higher levels of stress and anxiety while in segment NM_{I-IV}. This matches Participant 17 self-reporting lower low levels of trust in the (NM_{I-IV}, Trust Score: 1) segment compared to segment (RT_{I-V}, Trust Score: 5).

While the EEG signal connection was strong, the EEG data can be corrupted by noise from the participant moving their head. The bottom plot of figure 5.18 shows the variance of the EEG signal. A large spike in the variance of the EEG data is caused by the participant moving their head significantly. When the variance is extremely low this indicates that the EEG was not maintaining a strong signal.

To remove noise from the data a filter was applied that removed EEG data when the variance was extremely high (>10000 volts^2) or extremely low (<55 volts^2). This low and high pass variance filter accounted for noise from participants moving their heads, or when there was a poor EEG signal from lack of connection (i.e. hair blocking contact with the scalp). Figure 5.19 shows Participant 17's EEG data before and after the variance filter is applied, and the sections of EEG data that were removed

to reduce noise. After the variance filter is applied the mean beta/alpha power in the $\mathrm{RT_{I-V}}$ segment decreases from 2.9 dB to 2.8 db and the spike from the participants sudden head movement is accounted for. The variance filter makes the difference in the mean beta/alpha power between the $\mathrm{NM_{I-IV}}$ and the $\mathrm{RT_{I-V}}$ segments more pronounced.

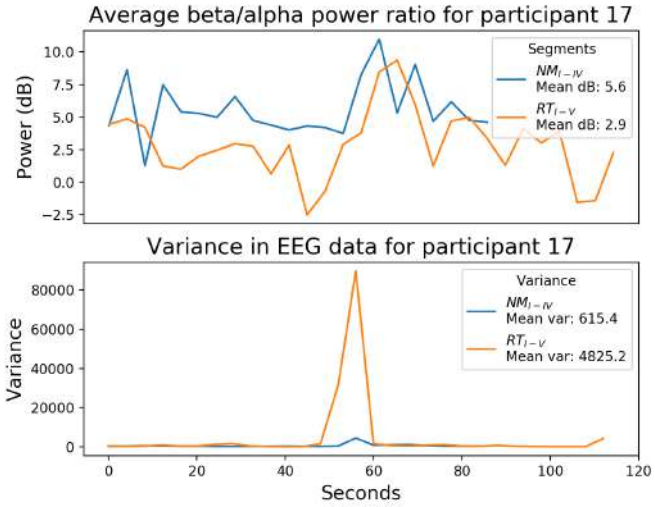


Figure 5.18: Participant 17 EEG data.

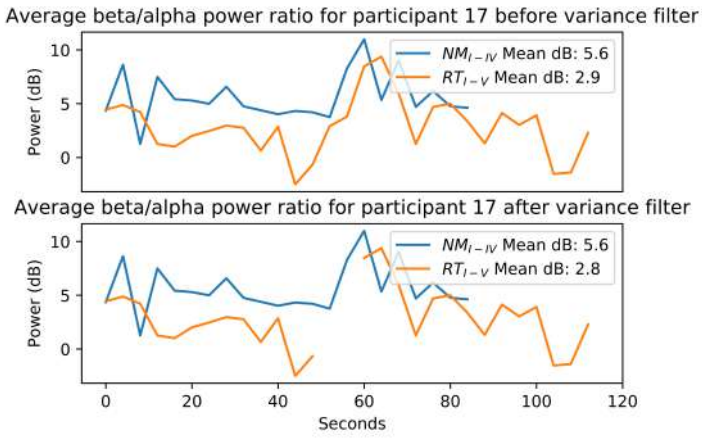


Figure 5.19: Participant 17 EEG data before and after the variance filter is applied.

EEG Analysis Scenario 1

The high and low pass variance filter was applied to all of the participant's EEG data. Figure 5.20 shows the mean beta/alpha power for all participants in Scenario 1 across segments after the data was cleaned with the variance filter. Figure 5.21 shows the change in the power of the mean beta/alpha power between segments for Scenario 1. From the TR_{I-II} to NM_{I-IV} segments the mean beta/alpha power is increasing (TR_{I-II} dB: -2.10, TR_{I-III} dB: -1.78, NM_{I-IV}, dB: -1.54), indicating that participants are feeling increasingly stressed and anxious. This is expected as the segments become increasingly stress-full, and this matches the subjects ratings of their mean trust in the SDC (TR_{I-II} Mean Trust Score: 3.72±0.68, TR_{I-III} Mean Trust Score: 3.68±1.25, NM_{I-IV} Mean Trust Score: 1.92±0.84).

As was predicted the NM_{I-IV} segment had the lowest mean beta/alpha power (-1.54 dB) for all participants, matching the lowest mean reported trust score of 1.92±0.84. In the RT_{I-V} a large increase in the mean beta/alpha power across participants is observed. An interesting observation is that the largest change in the beta/alpha power between segments occurs from NM_{I-IV} to RT_{I-V}. The largest change in how participants rated their trust levels also occurred between these two segments (NM_{I-IV} 1.92 ±0.84 to RT_{I-V} 3.96±0.92).

The only segment in Scenario 1 that deviated from expectation was the IT_{I-I} segment that had a mean beta/alpha power (-1.59 dB) that was higher then the TR_{I-II} -2.10 dB and TR_{I-III} -1.78 dB segments. It would be expected that the IT_{I-I} segment would have low beta/alpha power since participants reported having high levels of trust in the SDC in this segment IT_{I-I} 4.68±0.47. The IT_{I-I} segment was the participants first experience in the SDC simulator and there may have been increased stress due to becoming acclimated and comfortable with the simulator.

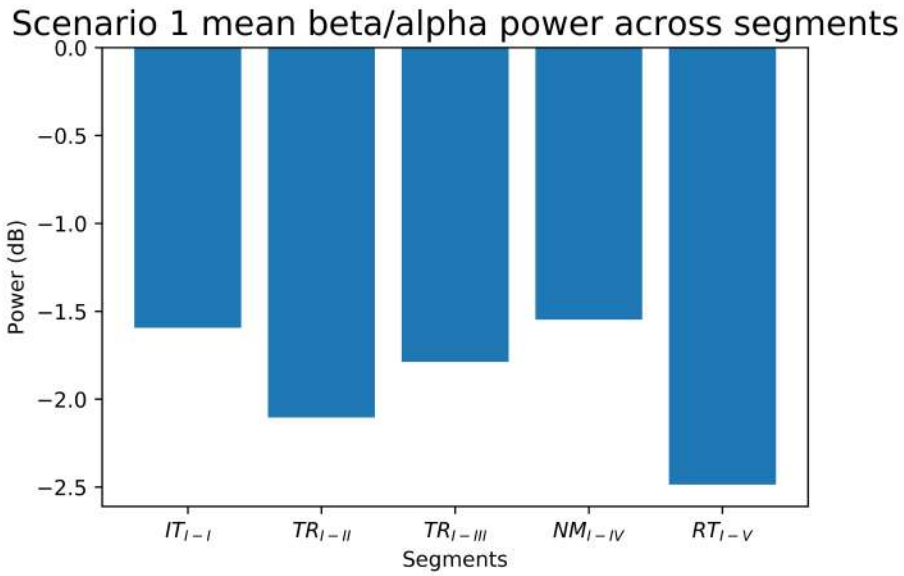


Figure 5.20: Scenario 1 beta/alpha mean power from all participants across segments.

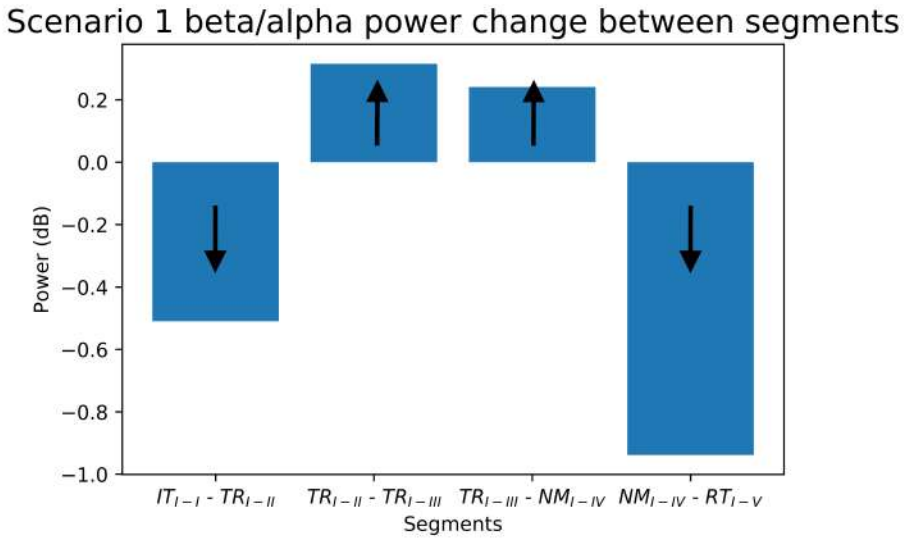


Figure 5.21: Scenario 1 change in beta/alpha power across segments. Arrows indicate if the power is increasing or decreasing.

EEG Analysis Scenario 2

Figure 5.22 shows the mean beta/alpha power for all participants in Scenario 2 across segments after the data was cleaned with the variance filter. Figure 5.23 shows the change in the power of the mean beta/alpha power between segments for Scenario 2. Scenario 2 did not perform as expected. It was predicted that in segments that did not induce stress or anxiety and that participants rated with high levels of trust in the SDC, IT_{II-I} 4.40±0.69, TE_{II-II} 4.64±0.68 and RT_{II-V} 4.04±1.11, a lower mean beta/alpha power would be observed, and in segments that elicit stress and anxiety and that participants rated with low levels of trust in the SDC, TR_{II-III} 3.68±1.12 and NM_{II-IV} 3.64 ±1.13, a higher mean beta/alpha power would be observed. This was not the case as segments IT_{II-I} -0.46 dB and TE_{II-II} -0.37 dB had relatively higher mean beta/alpha power compared to TR_{II-III} -0.83 dB and NM_{II-IV} -1.01 dB.

However, the anticipated effect of a decrease of mean beta/alpha power from a stressful to non-stressful segment was observed between segments NM_{II-IV} -1.01 dB and RT_{II-V} -2.47 dB. Between segments of Scenario 2 participants self-reported the largest change in trust levels to be between segments NM_{II-IV} 3.64 ±1.13 and RT_{II-V} 4.04±1.11, and we find that the EEG is able to capture the strongest effect between segments.

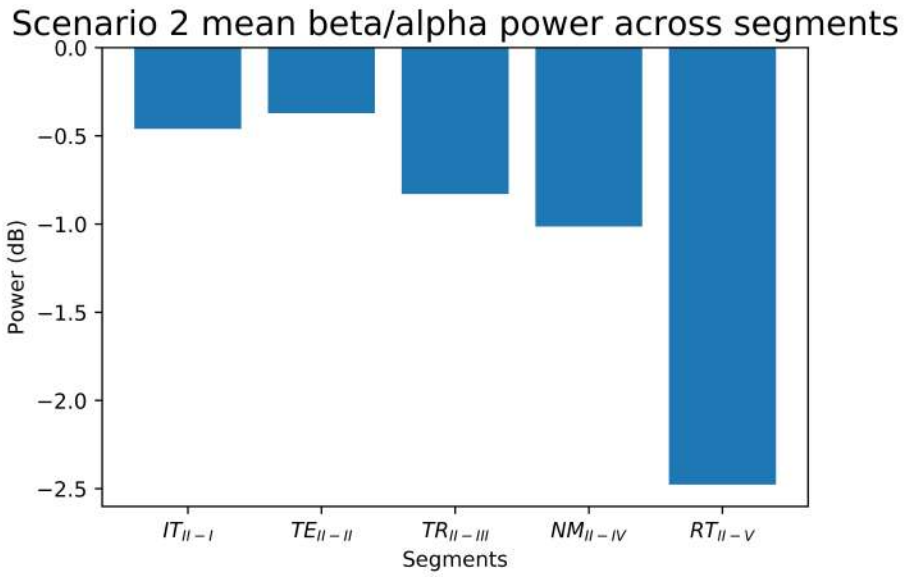


Figure 5.22: Scenario 2 beta/alpha mean power from all participants across segments.

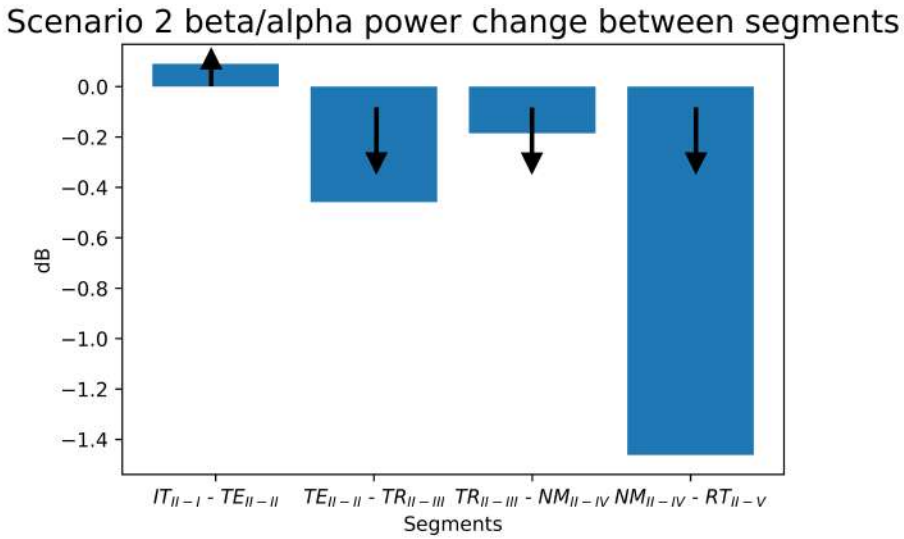


Figure 5.23: Scenario 2 change in beta/alpha power across segments. Arrows indicate if the power is increasing or decreasing.

EEG Analysis at moment of near collision

From the analysis of the EEG data in Scenario 1 and in Scenario 2 in 5.4.4 and 5.4.4 it appears that using the mean beta/alpha power to indicate if a participant is stressed or anxious is effective at capturing big effects, however misses more nuanced changes. Also attempting to capture an effect by averaging participants data over a long 2 minute time interval will be unable to resolve quickly changing conditions or events. A more precise alternative would be to analyze each individual participants EEG data at specific inflection moments.

Participants reported the lowest levels of trust in segment (NM_{I-IV}, Mean Trust Score: 1.92±0.84), and it contains the most stressful and trust damaging incident were the SDC malfunctions and nearly causes a car accident at an intersection. The incident is outlined in section 5.13. Since Participant 50 had the cleanest EEG signal, due to having a shaved head and limited head movement, this single participant's mean beta/alpha power during the stressful incident of nearly experiencing a car crash is plotted in figure 5.24. A much shorter time interval of 16 seconds is used to analyze the EEG data.

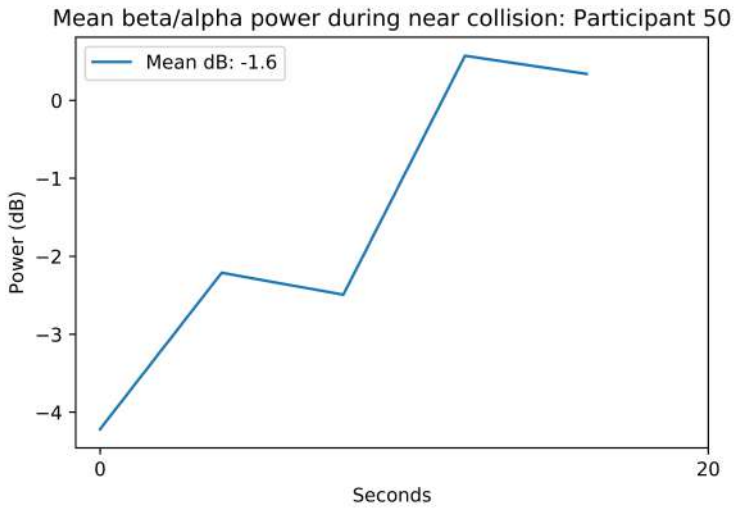


Figure 5.24: Beta/alpha power change at point of near collision inside the SDC simulator.

As anticipated a large increase in the mean beta/alpha power is observed during the small time window that coincides with the near car accident. Analyzing single participants at specific moments using small time intervals allows for more meaningful information retrieval. It is also worth noting that being able to selectively evaluate participants with clean EEG signals (primarily from having less interference due to hair on their head, and limited head movement) makes it easier to gain meaningful results.

CHAPTER 6
CONCLUDING REMARKS AND FUTURE DIRECTIONS

6.1 CONCLUSION

The results of the experiment were generally consistent with expectations. The participants reported higher trust levels after experiencing initial trust and trust escalation segments and reported distrust after the trust reduction segments, as well as high distrust after the negative trust mutation segment. An interesting observation was that participants especially did not trust the SDC around pedestrians.

The results of the experiment indicated that the trust levels of humans change depending on the SDCs driving style and that the majority of the participants were able to moderately rebuild trust in the simulated SDC car after faulty and erratic behaviors. Analysis of the demographic and survey questions indicates that demographic background did not have a significant effect on how passengers rated their levels of trust with the SDC. Certain psychological questions on trust did correlate with how passengers reported their levels of trust in the SDC. Participants that indicated they are more trustful, did report higher levels of trust in the SDC after each segment, and participants that indicated they are less trustful, reported lower levels of trust in the SDC after each segment.

Using the mean EEG beta/alpha wave band power as an indicator of feeling stress and anxious in a SDC appears to be effective when the stress inducing event is dramatic and strong within a small time interval, but becomes more difficult to obtain meaningful data when the incident does no elicit a very strong response or the time interval is long.

6.2 FUTURE WORK

This work used signal processing parameters for power spectral density estimates and the resultant EEG beta/alpha wave band power ratios based on a limited investigation of spectral processing methods, windows and overlaps. However, it may be that better results can be obtained by optimizing the signal processing parameters, and it is likely that parameters best suited for responsive detection of emotional changes in short intervals will differ from those that work best for longer-term emotional states. Studies indicate that independent component analysis techniques can been used to correct EEG signals from noise artifacts [57] [58].

EEG data has a low signal to noise ratio, therefore, it can often be difficult and time consuming to manually classify a data set, making a machine learning based classifier necessary for large sets of data. Prior research has shown that Linear SVM and MLP neural networks are good options to classify EEG data [59], [60]. Other physiological sensors (heart rate, skin perspiration, etc.) will be used in future work to detect stress. Perhaps EEG in combination with other physiological sensors will create a more robust system of detecting stress and anxiety in participants. Also future work will dedicate more time to analyzing the interaction of EEG signal with various electrode positioning.

Future work will implement a machine learning classifier to determine the subjects emotional state based on a combination of sensors. The ultimate goal is to lay the foundation to create a resilient supervisory feedback control module that monitors passengers state and acts as a feedback loop to modulate the control actions of the SDC.

APPENDIX

The results of this research appear in the following publications:

[1] Park C., Nojoumian M. and Pados D. A., Using EEG and Self-Reported Human Metrics to Measure Trust in Human-Autonomous Vehicle Interactions, 2018. (Under Review) [61]

[2] Shahrdar S., Park C. and Nojoumian M., Human Trust Measurement Using an Immersive Virtual Reality Autonomous Vehicle Simulator, 2018. (Under Review) [62]

[3] Park C., Shahrdar S. and Nojoumian M.,EEG-Based Classification of Emotional State Using an Autonomous Vehicle Simulator. 10th IEEE Sensor Array and Multichannel Signal Processing Workshop (SAM), pp. 297-300, Sheffield, UK, 2018. [22]

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