ANALYSIS OF DRIVING BEHAVIORS AND RELEVANT DRIVING PREFERENCES REGARDING SELF-DRIVING CARS

by

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ABSTRACT

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This thesis explores the cross-cultural demands from self-driving cars in regards to their trust, safety, and driving styles. Through the use of international survey data we establish several AI trust and behavior metrics that can be used for understanding cross-cultural expectations from self-driving cars that can potentially address problems of trust between passengers and self-driving cars, social acceptability of self-driving cars, and development of customized autonomous driving technologies. Further this thesis provides a serverless data-collection framework for future research in driving behaviors.

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CHAPTER 1

INTRODUCTION

In the last decade, it has become apparent that the technologies powering self-driving cars (SDC) are maturing at a rate that makes them a technological inevitability. The questions for the future then revolve around the adaptability of the technology rather than the technology itself. While self driving cars are a certainty, the large scale adoption of self-driving cars isn't so clear. Current research accordingly points to a grim outlook on people's perception of the technology. In 2021, Morning Consult surveyed 2200 adults in the United States and found that 47% of those surveyed believe autonomous vehicles are less safe than their human driven counterpart and that only 22% of those surveyed believe that autonomous vehicles are safer than a human driver [7]. With nearly half of the survey population having serious doubts about the technology on the precipice of its arrival, it becomes clear that research must be conducted in improving consumer trust in self driving cars. Yet the question still remains as to what is trust and how can one cultivate it within consumers of this technology. One method of cultivating trust for self driving cars is to improve on human-machine interaction, by designing self driving cars in a way that communicates to passengers and have them play a more active role in the experience one can deliver a more trustful system for users. This is supported by research conducted by Hartwich et al. where evidence suggests that even given a SAE Level 4-5 system where no human interaction is required, the introduction of monitoring tools significantly improves passenger trust [8].Further research conducted by Hartwich et al. shows that the significance of the first experience with self driving cars greatly impacts the trust one associates with the technology [9]. In addition to the first experience being significantly impactful to a users perception of the technology, research from Shahrdar et al. shows how trust is greatly affected by the driving style used and that defensive driving builds more trust than aggressive driving in virtual reality simulated tests [10][11]. These tests also showed that while initial experiences were important, trust in the system can be rebuilt following a faulty behavior given enough time experiencing safer and more defensive driving from the self-driving car. The amount of control a user haves seems to play strongly into a users ability to trust a given system. It is well known in the classical scenario of a person being chauffeured that there is an increased level of discomfort while being a passenger as compared to an active driver [12] and it appears that this analogue translates very well to the self driving car scenario. Yet there is still a decreased amount of trust for robotic drivers versus a human driver given equivalent driving behaviors as shown in Mühl et al. [13]. This poses that not only do self driving cars have to perform as well as a human driver, but better in order to gain as much trust from their passengers. Beyond increasing the interactions passengers can experience with a self-driving car one can also modify the driving style in order to increase trust in the system. Research conducted by Basu et al. showed that a more defensive driving style led to higher trust in autonomous driving scenarios [14]. Interestingly, when participants were surveyed on their driving preferences they responded that they would want an experience similar to their own driving style for a self driving car. Yet, when passengers were placed in a simulation it was found that they preferred a driving style that they thought was their own but instead was much more conservative than their own driving style [14]. Similar results were observed by Craig et al. where surveyed participants showed that they expect a self driving car to behave as in a slightly less aggressive manner than their own driving style [5]. Methods proposed by Park et al. suggest adapting the driving behavior based on EEG feedback in order to establish and maintain trust in the system [15]. With these questions in mind we must further consider how users will respond with these technologies outside of the demographics in which research is collected. There is a great question as to how research participants are biased by the infrastructure and cultural norms of the country in which research takes place. There are some surveys that provide an international view such as research conducted by Deloitte in 2020. This survey provided responses by country (South Korea, Japan, United States, Germany, India, China) detailing the percentage of consumers who believe SDCs will not be safe. The results provided by Deloitte for most countries follow United States sentiments ($\sim$ 50% belief they will not be safe) with some outliers, such as China whose survey data suggests a more trusting sentiment and India whose survey data suggests a less trusting sentiment [16]. With the majority of self-driving car (SDC) research being conducted and tested domestically within the United States from the likes of Tesla and many silicon valley startups, it becomes challenging to understand the global needs of this technology. This thesis therefore proposes to shed light on cross-cultural expectations from autonomous vehicles. We utilized a survey with 57 questions, prepared in English, German, and Spanish languages, that asked 157 participants about their personal driving behaviors as well as their expectations from SDCs. The respondents totaled 52 from the United States, 64 from Germany, and 41 from Central America. Interestingly, we observed that German drivers are slightly *more aggressive* than American drivers; however, when it comes to SDCs, both groups have the same expectation from SDCs, i.e., prefer a SDC that operates like a *less aggressive version of their own driving behaviors.* This is consistent with prior research outcomes in the United States [5]. On the other hand, Central Americans expect a *very conservative driving behavior from SDCs compared to Americans and Germans.* The first observation might be due to the fact that faster driving is allowed in Germany, e.g., highways with no speed limit; however, since fully-autonomous driving technology still hasn't been deployed and is unknown, both groups expect less aggressive SDCs. The second observation may indicate that more exposure to autonomy, which is now happening in the United States and Germany as opposed to developing countries, can gradually prepare the society to trust and accept these emerging autonomous technologies. These are possible hypotheses, among others, although frequent data collections and analyses in larger scales are required to validate and justify these fascinating observations. Other interesting observations are illustrated in the paper. With the problem sufficiently motivated, the goal of this thesis is then to understand driving behaviors of prospective users internationally and establish a metric for user trust and desired driving behavior within autonomous vehicles. Further once a trust metric is generated, this thesis proposes a methodology for relating a users driving preferences to the AI driving task in order to provide a driving experience more consistent with their own driving expectations.

CHAPTER 2

LITERATURE REVIEW OF SELF-DRIVING CAR TECHNOLOGY

2.0.1 Automated Highways

The history of self-driving car technology dates back nearly a century at this point. The 1939 World's Fair provides an early description fully autonomous vehicles in the form of Norman Bel Geddes's Futurama exhibition which displayed a miniature city with sprawling highways connecting the metropolitan cityscapes to the remote farmlands, remember at this time the interstate highway system has not been constructed yet. In this exhibit cars are guided through highway routes using electromagnetic fields generated along the highway which dictated the direction of steering for the car allowing for the cars to stay within a given lane as well as change lanes when needed [1]. An image showing the exhibits city highways can be seen in figure 2.1.

Figure 2.1: Futurama Exhibit from the 1939 World Fair [1]

However it wasn't until 1960 when the UK Transport and Road Research laboratory modified a Citröen DS to steer without driver assistance using guidance from magnetic rails hidden under the road [17] did the visions of the future shown in 1939 start to come to life. The work done by the UK Transport and Road Research laboratory represented the first real glimpse into the future of self driving cars; yet, at this point the future of self driving cars seemed to be one based on infrastructure solutions rather than the cars themselves. While these ideas were novel and challenged the status quo for driving, clear issues in scaling such such a project will arise. Through the mid 1900s we will see a steady transition from self-driving cars being envisioned the product of radio and electromagnetic systems with large scale infrastructure to one of computer and visual technology manifest into cars themselves.

2.0.2 AI for Self Driving Cars

Once computing became mainstream and AI hit its first major stride in the and 80s and 90s the idea of cars self navigating started to become a reality. Two main efforts in this field occurred in the form of the NAVLAB project out of Carnegie-Mellon [18] and the VaMoRs project out of Mercades [19]. Both of these projects were revolutionary in the usage of computer vision for vehicle navigation. At this point in time image segmentation was extremely rudimentary, NAVLAB's segmentation technique would consider the probability a given pixels color belonged to the road in order to segment road from other objects in the frame [20]. This allowed for NAVLAB to identify road and apply geometric transforms on a given image in order to determine the pathing required to stay on the road. Later versions of the NAVLAB during this time begin to employ the first neural networks being designed for the self driving task. Famously ALVINN: An Autonomus Land Vehicle in a Neural Network was able to map video images to vehicle actions using a simple 2 layer fully connected neural network [2]. The system out of Mercades was similarly built, named VaMoRs, the Mercedes self

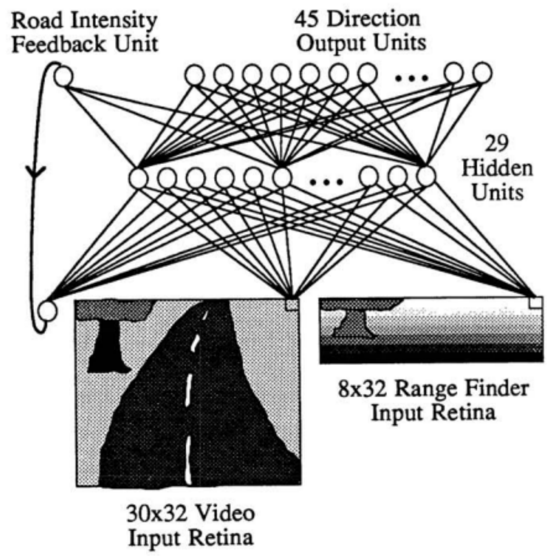

Figure 2.2: ALVINN Neural Network Architecture [2]

driving car used cameras and image processing techniques to track objects and road paths. In comparison to later versions of NAVLAB, the VaMoRs system used more traditional image processing techniques and complex filters in order to do object detection and tracking. Regardless of the methodology used, it was at this point in time that it was clear that the future of self driving cars will heavily rely on visual data processing. As we approach the early 2000s we enter a new paradigm shift in technologies where high resolution GPS data becomes available to the masses as well as high resolution maps. These features will eventually become a mainstay in self driving car technology. During this period we also see the introduction of the DARPA grand challenges which was a set of contests to build autonomous vehicles that can traverse difficult desert terrain. College students from Stanford were able to build a fully autonomous vehicle, dubbed Stanley, that was able to traverse a 175 mile long desert course with vast shifting terrain in under 10 hours [21]. Stanley was able to achieve this through a mix of cameras, lasers, and radar systems. At Stanley's core was an understanding of the vehicles state described by it's position, velocity, orientation, accelerometer biases, and gyro biases and how that state should respond to the world through probabilistic models. Towards the mid 2000s we begin to see testing of autonomous vehicles using high resolution LiDAR sensors, these sensors are able to produce very precise distance maps of the 3D space which is incredibly useful for the self driving task. Companies such as Waymo and other large players in the self driving car space has invested heavily in LiDAR technology as the main sensor used for their self driving cars [22].

2.0.3 Deep Learning

As computational power increased over the coming years and machine learning innovation really started taking off in early 2010s, more powerful visual algorithms were able to be implemented such as those heavily dependent on large convolutional neural networks. The rise of deep learning during this period has enabled rapid growth and confidence in autonomous vehicle technology. One such framework at the core of most visual systems today is You Only Look Once or YOLO by Joseph Redmon which provided a paradigm shift for visual machine learning [3].

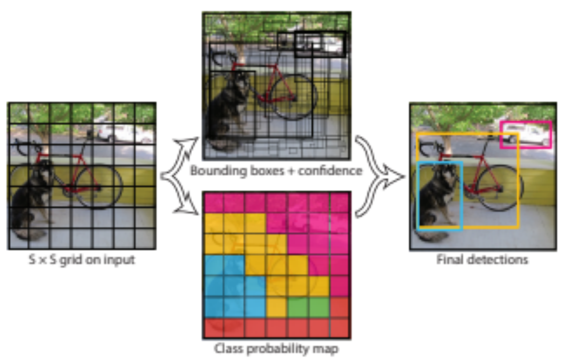

Figure 2.3: Example of the YOLO model performing object detection [3]

Prior to YOLO the visual systems being used in self driving cars heavily relied on edge detection and traditional image processing techniques such as filtering in order to parse objects from each frame. Advancements in computer vision such as YOLO has given industry leaders such as Tesla enough confidence to go fully into visual based autonomous driving with their own proprietary Tesla Vision [23]. Other industry leaders have been more hesitant in the transition to full visual systems believing the best solution will be a mix of cameras and LiDAR systems.

2.0.4 Levels of Autonomy

The previous sections have described the several advancements in the field of autonomous vehicles, with each of these advancements comes higher levels of autonomy possible for a self driving car. The Society of Automotive Engineers (SAE) have defined a hierarchy of driving automation on a 0 to 5 scale where 0 represents a fully manual vehicle and 5 represents a fully autonomous vehicle [24]. Details about this scale and what each level fully entails can be seen in figure 2.4.

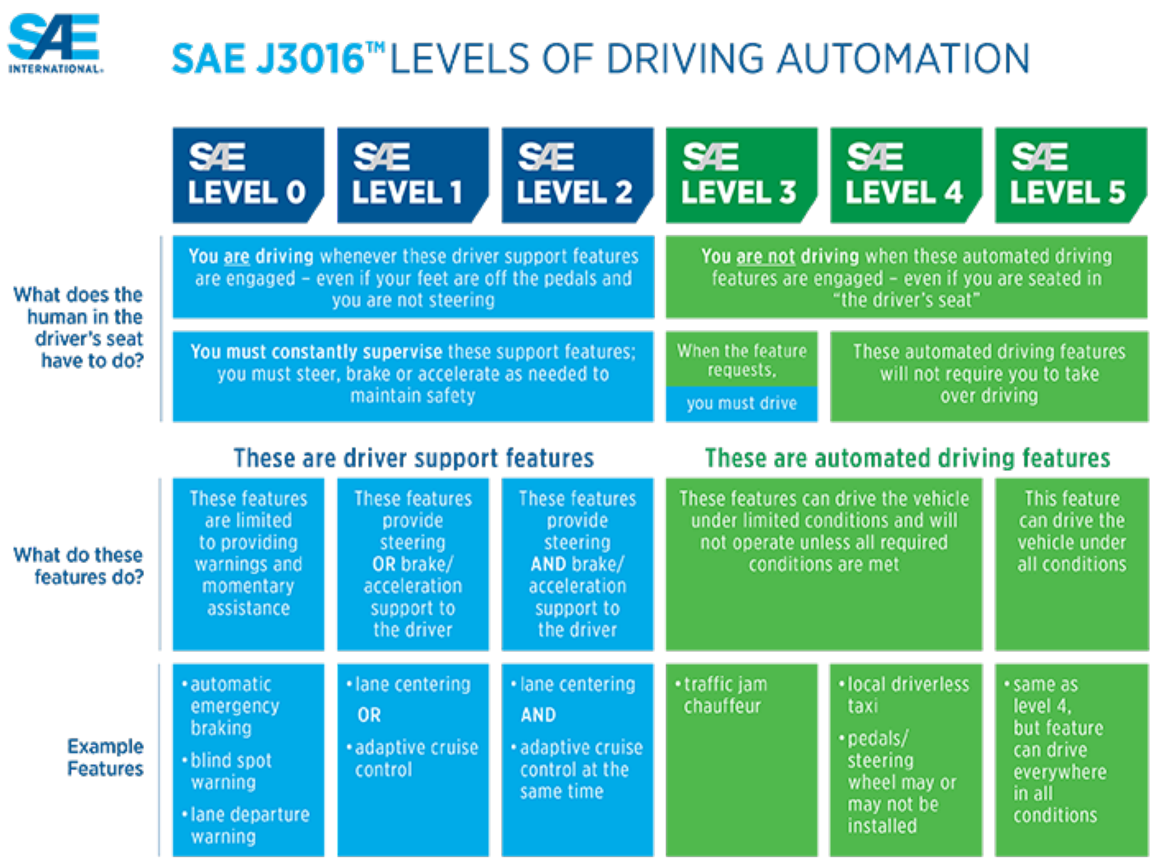

Figure 2.4: SAE Levels of Automation [4]

Currently on the road today, Mercedes-Benz's "Drive Pilot" represents a level 3 automation system which is able to fully handle the driving task under well defined areas at slow to moderate speeds [25]. There are some level 4 automated systems being used under highly restricted conditions today and its becoming more likely that we will see level 4 systems on the road in the coming decade. Level 5 systems however are still far from being a reality due to the number of edge cases such a system would need to handle. Beyond any technical limitations there are also a slew of legal issues that arise with highly autonomous systems. Mainly there is no clear consensus on to who accepts liability for the accidents that are inevitably going to occur. In the case of semi-autonomous systems the lines are blurred even further to who should accept liability. Research from Awad et al. suggests that drivers are blamed more than the automated systems in these semi-autonomous situations even when both make errors [26]. At some point certain legal standards need to be accepted in which liability is shifted to the automobile manufacturer if they certify a certain level of autonomy on their cars, what those standards are however have yet to be decided.

2.0.5 Trust in Self Driving Cars

Up until now the story of self driving cars has been focused entirely on the technical aspects. With the advancements described in deep learning and high resolution sensors autonomous driving at scale has more-or-less already arrived. Yet with this new territory comes questions of trust that need to be addressed. With self-driving cars comes modern day trolly problems where the self driving car will need to make decisions that will either maximize the safety of its passengers or of external humans. Survey studies have shown that people want utilitarian autonomous vehicles [27]. The issue of course arises that any utilitarian framework puts the owner of the self driving car at risk under certain conditions. Shariff et al. [28] proposes that the discussion of risk needs to be posed in terms of "absolute risk" rather than relative risk as by driving a self-driving car your total risk of injury is diminished therefore you shouldn't worry too much about the edge cases where your safety may not be prioritized. When considering things from an absolute perspective users may be more likely to buy into a self-driving car as their chances of survival on any given drive are overall maximized by doing so. There are also questions as to whether such utilitarian views are universal across all cultures and whether or not the utilitarian view is one of virtue signaling or of true sentiment.

2.0.6 Comfort as a Passenger in Self Driving Car

Yet another challenge self driving cars must overcome beyond any technical challenges is that the driving behavior must feel natural to a given passenger. How a self-driving car drives may feel riskier than what a human passenger is comfortable with. Studies from Kolekar et al. suggest self-driving behavior can be made more human like with the introduction of "driver risk field" modeling where the cars behavior is tuned to a given drivers perceived risk when executing driving maneuvers [29]. This generates autonomous behavior that is more in line with human driving than the current status quo which only tries to minimize the real risk proposed from a driving scenario.

2.0.7 Adoption of Self Driving Vehicles

Adoption of self driving cars seems to be entirely dependent on the few factors discussed. The first being the self driving cars ability to truly provide a self driving experience with little to no human intervention, having that experience be trusted, and finally having an experience that minimizes uneasiness as a passenger. Until these factors are met it is unlikely self-driving cars will see mass market adoption.

CHAPTER 3
SUBJECTIVE DATA COLLECTION OF DRIVING BEHAVIORS AND EXPECTATIONS

3.1 METHODS IN SUBJECTIVE DATA COLLECTION

3.1.1 Subjective Data Collection for Driving Behavior and AI Trust

The following sections describe a survey conducted in order to determine metrics for a users preferred driving style and how they would prefer an autonomous vehicle to perform. Further, this survey was conducted internationally in order to understand the demands of users across various areas. Through subjective data collection methods this thesis attempts to create measurable metrics for a variety of driving behaviors and trust.

3.1.2 Novelty of Our Approach

The novelty in our approach revolves around the cross-cultural aspects of our data collection and analysis. As stated earlier, we surveyed 157 people across the United States, Germany, and Central America that were recruited through local-networking and through PollPool.com. Survey data was systematically translated from English to the other targeted demographics primary language, mainly German and Spanish. The respondents totaled 52 from the United States, 64 from Germany, and 41 from Central America. This analysis was the first to collect cross-cultural data regarding driving behaviors and passengers' expectations from autonomous vehicles. Our analysis provides the first international examination of trust and driving behaviors contrasting a European and Central American sentiment with respect to the United

States sentiments of self-driving cars. It expands upon current research allowing for trust-based and behavior-based metrics to be extracted from data.

3.1.3 Subjective Data Collection Procedure and Instruments

Participants were asked to fill out a survey. The survey asks 57 questions relating to demographics, personal driving behaviors, and trust as it relates to AI and self driving cars. The survey was structured into 7 distinct sections as follows:

- **Section 1** provides demographic information including data about what country the driver currently resides in and what country they have driven the most in as well as age, gender, ethnicity, education, employment status, income range, etc.

- **Section 2** provides information regarding how a driver behaves on non-highway roads and it is used to define an aggressiveness score of the driver.

- **Section 3** provides information regarding how a driver behaves on highway roads and it is also used to define an aggressiveness score of the driver.

- **Section 4** provides information regarding general driving behaviors such as parking, turning, and driving under difficult weather conditions.

- **Section 5** provides information regarding how drivers currently trust Artificial Intelligence (AI) and its applications to self-driving cars on a set of fuzzy trust states: distrust, somehow distrust, neutral, somehow trust, and trust.

- **Section 6** provides information regarding how drivers expect AI/autonomy to perform on non-highway roads.

- **Section 7** provides information regarding how drivers expect AI/autonomy to perform on highway roads.

3.1.4 Quantitative Measurement

Each question asked can be related to a quantitative value in order to define a *Driving Behavior Aggressiveness* (DBA), *Self-Driving Car Aggressiveness* (SDCA), *AI Driving Mechanics Trust* (AIDMT), general *AI Trust* (AIT), and *Driver Safety Score* (DSS) metrics. A sample of a given question and its encoding can be found in Figure 3.1. Each question's encoded score can be valued between 0 and 1, where a score of 0 represents a cautious/conservative action, a score of 0.5 represents a moderate action, and a score of 1 represents a more aggressive action.

Question: Which best describes your behavior most of the time in terms of speed while driving on: THE HIGHWAY	**Aggressiveness Score**
I typically drive under the speed limit (more than 5 mph UNDER the speed limit)	0
I typically drive the speed limit (with plus or minus 5mph)	0.5
I typically drive over the speed limit (more than 5 mph OVER the speed limit)	1

Figure 3.1: Sample question to define DBA score [5].

Responses from highway based and non-highway based questions are averaged together to provide a more general scoring of the drivers aggressiveness in all situations. The same method was applied to questions related to SDCA questions across highway and non-highway questions. A generalized DBA score and SDCA score are found from averaging the results in each respective category. For DBA scores, a score of 0 represents a conservative driver and a score of 1 represents an aggressive driver. For SDCA scores, a score of 0 represents a conservative SDC and a score of 1 represents an aggressive SDC. These scores can then be used to contrast expectations of a SDC to their own driving behaviors. From the survey, a total of 20 questions were used to determine a driver's average DBA and SDCA scores. 16 questions were used to determine a driver's trust towards the AI's ability to execute driving mechanics and defined as the AI Driving Mechanics Trust (AIDMT) score. Driver Safety Score (DSS) was evaluated using 10 questions that are correlated with safe driving behaviors, a lower score is associated with safer driving behaviors. Finally, 7 questions were used to describe a driver's general trust of AI technology and its ability to perform in rare and complex environments. These questions define the AI Trust (AIT) score. In order to ensure our metrics are measuring different aspects of a respondents driving profile we consider the correlation between their responses. Figure 3.2 shows the Pearson correlation between each measured metric across all demographics. From this we can see that most metrics share a very weak to no correlation with each other with the exception of AIT and AIDMT which are slightly correlated with a correlation coefficient of .66. In general a respondent who is more trustful of AI tends to trust it's ability to perform driving mechanics. This correlation is strongest within the German population with a coefficient of .73 seen in Table 3.5.

	DBA	SDCA	AIT	AIDMT	DSS
DBA	1.000000	0.302058	-0.102445	0.027365	0.423913
SDCA	0.302058	1.000000	0.310328	0.286854	0.555095
AIT	-0.102445	0.310328	1.000000	0.664580	0.054697
AIDMT	0.027365	0.286854	0.664580	1.000000	0.143085
DSS	0.423913	0.555095	0.054697	0.143085	1.000000

Figure 3.2: Pearson Correlations between Each Metric Across All Demographics.

	DBA	SDCA	AIT	AIDMT	DSS
DBA	1.000000	0.251073	0.015642	-0.081609	0.414427
SDCA	0.251073	1.000000	0.359044	0.310139	0.563575
AIT	0.015642	0.359044	1.000000	0.620358	0.105442
AIDMT	-0.081609	0.310139	0.620358	1.000000	0.015133
DSS	0.414427	0.563575	0.105442	0.015133	1.000000

Figure 3.3: Pearson Correlations between Each Metric for US Respondents.

	DBA	SDCA	AIT	AIDMT	DSS
DBA	1.000000	0.353846	0.039435	0.157695	0.480262
SDCA	0.353846	1.000000	0.299758	0.100525	0.556005
AIT	0.039435	0.299758	1.000000	0.655622	0.016596
AIDMT	0.157695	0.100525	0.655622	1.000000	-0.017889
DSS	0.480262	0.556005	0.016596	-0.017889	1.000000

Figure 3.4: Pearson Correlations between Each Metric for Central American Respondents.

	DBA	SDCA	AIT	AIDMT	DSS
DBA	1.000000	0.261877	-0.291075	-0.109018	0.369755
SDCA	0.261877	1.000000	0.234835	0.213029	0.409340
AIT	-0.291075	0.234835	1.000000	0.727642	-0.084054
AIDMT	-0.109018	0.213029	0.727642	1.000000	-0.098955
DSS	0.369755	0.409340	-0.084054	-0.098955	1.000000

Figure 3.5: Pearson Correlations between Each Metric for German Respondents.

3.1.5 Consistency in Measurement

In order to measure the consistency of our survey across each measured score we consider the Cronbach's Alpha values for each survey section where a measured quantity was calculated for each demographic. The number of items in each metric measured is shown in the table 3.1. The alpha values allow us to determine how closely questions

	Number of Items
DBA Highway	5
DBA Non-Highway	5
SDCA Highway	5
SDCA Non-Highway	5
AIDMT Highway	8
AIDMT Non-Highway	8
DSS	10
AIT	7

Table 3.1: Number of items used in each section

are related to one another in a group of questions. One should expect the consistency of a group of questions to be invariant to the language in which the question is asked; however, we observe differences in alpha values across surveys in various languages.

3.1.6 Cronbach's Alpha Values

We first consider the alpha values for each language and region the survey was offered in. Table 3.2 shows the Cronbach's Alpha values for each section for US respondents. The number of items for each question grouping is relatively small; however, we should expect similar consistency across groupings of similar questions. What was observed however provides different consistency of responses depending on the context in which the question is asked. Of note when respondents were asked the same questions in a highway setting versus a non-highway setting the consistency of their answers was negatively impacted as reflected in the low α values calculated with respect to their non-highway responses compared to their highway responses. Further when respondents were asked the same question in the context of a self driving car performing the action, the consistency of their answers in regards to the metric examined increased drastically. The phrasing used for DBA scores and SDCA scores for a sample question is shown in figure 3.6. The German Cronbach's Alpha values can be seen in Table 3.3. These values follow the US respondent values closely in most groups. Non-highway based DBA questions for German respondents produced a significantly lower α value as compared to US respondents. The Central American Cronbach's Alpha values can be seen in Table 3.4. Compared to the US and German respondents the Central American respondents measured a much lower alpha value for the DBA scores and much higher alpha values for each other metric measured. The variations in alpha values across demographics yields some interesting questions as to how context affects the relevance of question groupings. These factors may be explained by differences in highway vs non-highway constructions in those demographics as well as what is considered aggressive driving under said context. Exploration in the factors driving these variations is a primary question of future research efforts.

DBA Sample Question	SDCA Sample Question
Which best describes your driving behavior most of the time in terms of speed while driving on: THE HIGHWAY	If you are traveling in a self-driving car, and the car is in control of the speed, what range speed would you feel most comfortable with when driving on: HIGHWAY ROADS

Figure 3.6: DBA Score Question and SDCA analogue

	α	95% CI	80% CI
DBA Highway	.487	[.222, .682]	[.327, .624]
DBA Non-Highway	.306	[-.052, .569]	[.089, .491]
SDCA Highway	.782	[.671, .865]	[.715, .841]
SDCA Non-Highway	.700	[.546, .814]	[.607, .781]
AIDMT Highway	.905	[.824, .925]	[.846, .912]
AIDMT Non-Highway	.881	[.859, .940]	[.877, .930]
DSS	.535	[.316,.705]	[.401,.654]
AIT	.879	[.82,.924]	[.843,.911]

Table 3.2: US Respondents Cronbach's Alpha Scores

	α	95% CI	80% CI
DBA Highway	.531	[.325, .689]	[.405, .641]
DBA Non-Highway	.062	[-.350 .378]	[-.190, .282]
SDCA Highway	.758	[.651, .839]	[.692, .814]
SDCA Non-Highway	.682	[.543, .789]	[.597, .757]
AIDMT Highway	.883	[.835, .921]	[.853,.910]
AIDMT Non-Highway	.865	[.810, .909]	[.831, .896]
DSS	.451	[.231,.629]	[.315, .575]
AIT	.900	[.857,.932]	[.873, .922]

Table 3.3: German Respondents Cronbach's Alpha Scores

	α	95% CI	80% CI
DBA Highway	.183	[-.292,.520]	[-.103,.422]
DBA Non-Highway	.166	[-.320,.510]	[-.126,.410]
SDCA Highway	.861	[.781,.919]	[.813,.902]
SDCA Non-Highway	.812	[.703,.890]	[.746,.867]
AIDMT Highway	.957	[.933,.974]	[.942,.969]
AIDMT Non-Highway	.956	[.932,.973]	[.949,.968]
DSS	.434	[..145,.664]	[.261,.598]
AIT	.959	[.937,.976]	[.946,.971]

Table 3.4: Central American Respondents Cronbach's Alpha Scores

3.2 SUBJECTIVE DATA COLLECTION RESULTS

This section compares the scores generated from each of the defined quantitative metrics (DBA, SDCA, AIDMT, AIT, and DSS) against the collected demographic data in order to verify if there is a statistically observable difference across demographics within a nation's population as well as from an international perspective.

3.2.1 International DBA and SDCA Metrics Across all Demographics

Across all surveyed respondents, the following summary statistics were generated describing the distributions of quantitative metrics DBA, SDCA, AIDMT, AIT, and DSS as shown in Table 3.5. These summary statistics include the mean, standard deviation, median, min and max values across all regions where surveys were distributed.

	DBA	SDCA	AIT	AIDMT	DSS
Mean	0.428	0.341	0.478	0.551	0.312
Standard Deviation	0.139	0.193	0.247	0.252	0.139
Median	0.450	0.350	0.500	0.547	0.300
Min	0.075	0.00	0.00	0.00	0.050
Max	0.750	1.00	1.00	1.00	0.675

Table 3.5: International summary statistics.

The following DBA and SDCA scores were generated and can be seen in Figure 3.7. From this distribution, we can see that across all nations surveyed most drivers behave in a conservative to moderate fashion and most drivers will lean towards having a far more conservative self-driving car compared to their own driving behaviors. This finding supports previous research conducted in [5], which provided similar distributions across these metrics. Using the Mann-Whitney U Test, we can statistically confirm that these distributions are statistically different with a p-value of 0.000. These distributions are shown in Figure 3.7. Further, we can compare the two new metrics introduced for this analysis, general AI Trust and AI Driving Mechanics Trust. These distributions can be seen in Figure 3.8. Of note, we can observe a clear divide between somewhat trust and somewhat distrust in the driver's AIT score. This is contrasted against the driver's AIDMT score, which shows a flatter distribution with a somewhat trust bias.

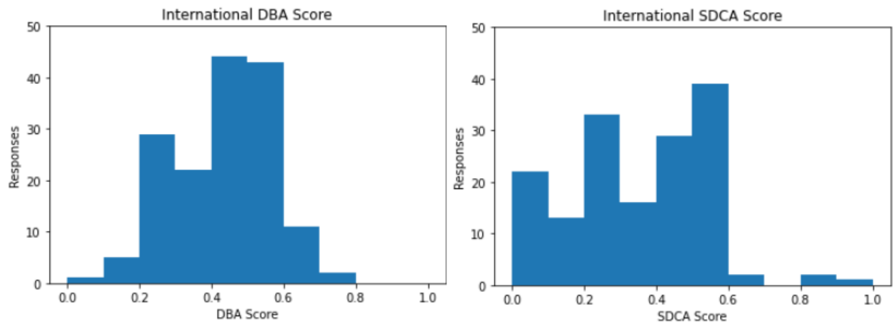

Figure 3.7: International DBA and SDCA histograms.

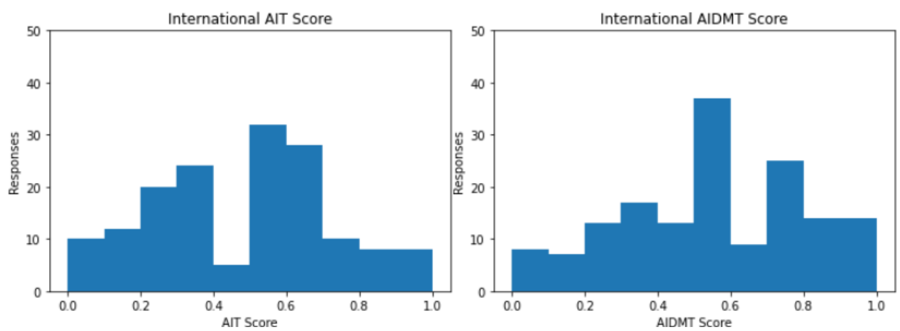

Figure 3.8: International AIT and AIDMT histograms.

3.2.2 International Metrics Across Genders

For this analysis, we consider if there are any significant differences in the quantitative metrics defined across genders. Using the Mann-Whitney U test, we found that there is no statistically significant difference in DBA or SDCA scores across genders for the international respondents. There is however a statistically significant difference between gender when it comes to AIT and AIDMT with p-values of $2.84E-05$ and 0.0004, respectively.

The plots, represented in Figure 3.9, illustrate a clear difference in AI trust across genders internationally with *females being less trustful of AI technology* in both a general sense and in its ability to perform several driving mechanical functions.

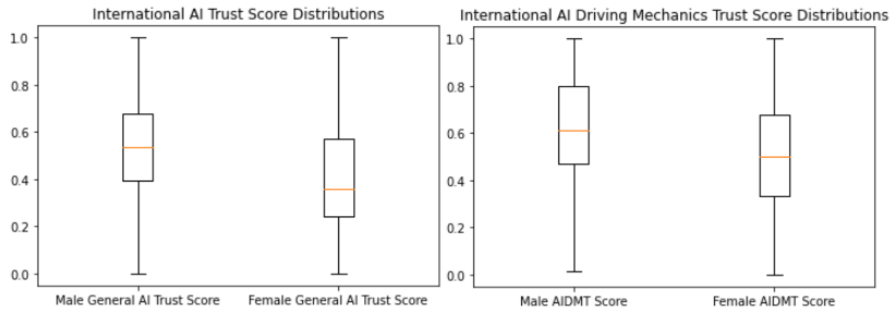

Figure 3.9: International AIT & AIDMT for males vs females.

3.2.3 International Trust Levels and Driving Aggressiveness

Of interest to this analysis is the relationship between people's trust in AI and how they would like their SDC to perform. For this analysis, we considered a driver with an AIT score of less than or equal to 0.5 to be generally distrustful of AI technology while a driver with a trust score greater than 0.5 to be generally trustful of AI technology. Under these parameters, the following SDCA score distributions are reproduced in Figure 3.10. Using the Mann-Whitney U Test, we compared these distributions against the international DBA score to see how the distributions are related.The comparison of the SDCA of drivers, who are distrustful of AI technology, to their own driving behaviors shows a p-value of 0.000 agreeing with the general result that people want a SDC that is *more conservative than their own driving behavior.*

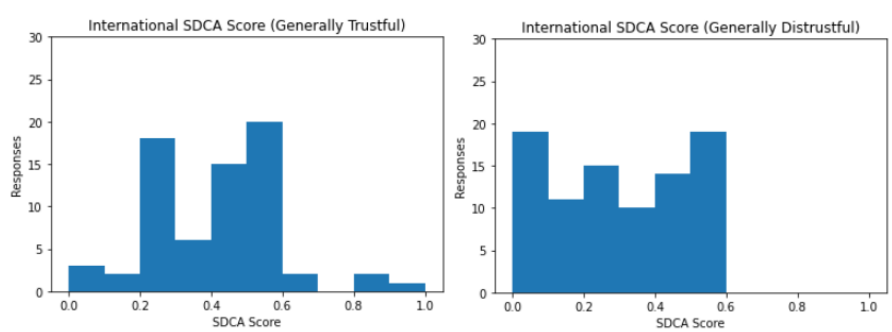

Figure 3.10: International SDCA scores for trustful and distrustful drivers based on AIT scores.

However, this result changes when we consider the SDCA of drivers, who are trustful of AI technology, to their own driving behavior. In this case, we failed to reject the null-hypothesis and show that there is evidence for these drivers preferring a SDC that mimics their own moderate driving behaviors. This is fascinating and confirms that social acceptability of SDCs is a challenge even among people who trust AI technology. These results are also examined when comparing the correlated AIDMT score to the SDCA score under the same trust split showing similar results as illustrated in 3.11

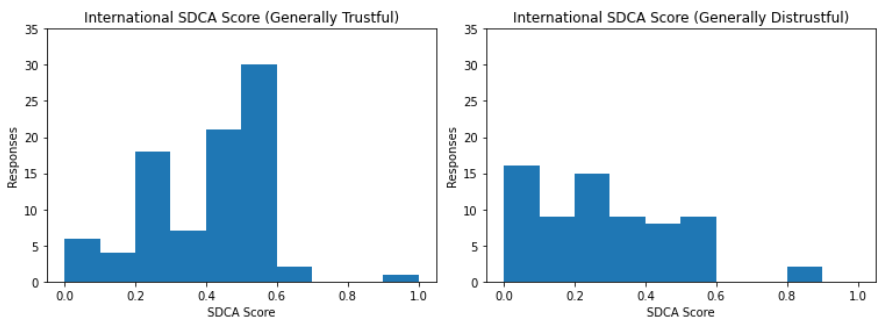

Figure 3.11: International SDCA scores for trustful and distrustful drivers based on AIDMT score.

3.2.4 American Respondent Analysis

Across all American surveys we consider the responses evaluated across each metric DBA, SDCA, AIT, AIDMT, and DSS. The summary statisitcs provide the mean, standard deviation, median, min and max observed values and can be seen in Table 3.6.

	DBA	SDCA	AIT	AIDMT	DSS
Mean	0.409	0.386	0.536	0.627	0.358
Standard Deviation	0.148	0.203	0.226	0.225	0.135
Median	0.45	0.4	0.536	0.609	0.363
Min	0.1	0.0	0.071	0.02	0.100
Max	0.7	1.0	1.0	1.0	0.675

Table 3.6: American summary statistics.

This analysis further considers if there exists the same difference in preference when comparing DBA and SDCA scores for American respondents. From the plots shown in Figure 3.12, we observe that there isn't a large contrast between their own driving behavior and what they expect from a SDC. When run through the Mann-Whitney U test, we failed to reject the null-hypothesis when comparing these two distributions. The DBA and SDCA scores from American respondents can be seen in Figure 3.12.

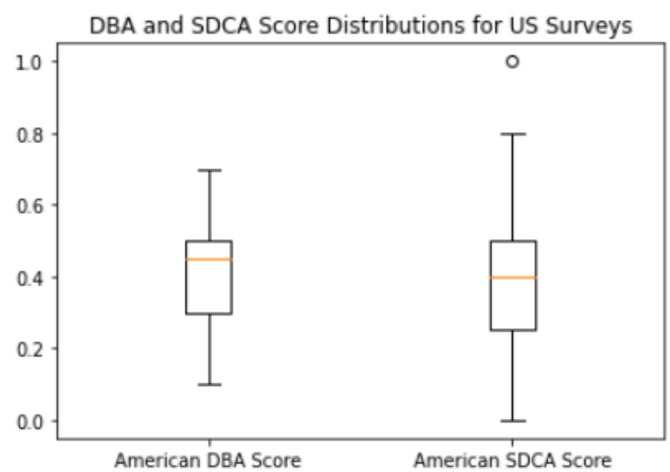

Figure 3.12: American DBA and SDCA score comparison.

The DBA and SDCA scores provide evidence that *Americans prefer their SDCs to behave more like their own driving behavior*.

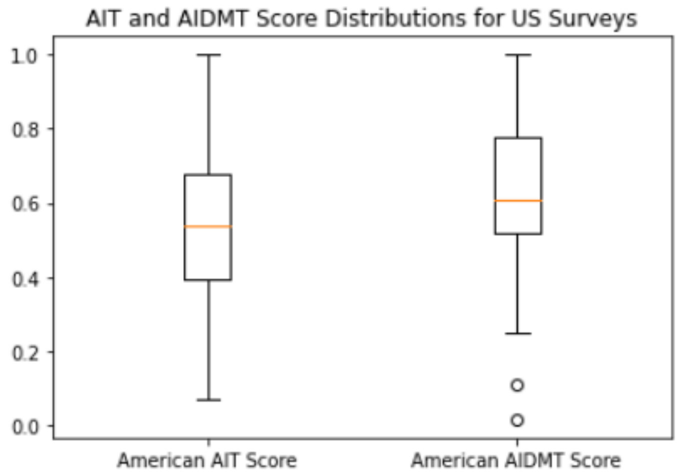

Figure 3.13: American AIT and AIDMT scores.

The two trust metrics AIT and AIDMT were produced and shown in Figure 3.13. These trust metrics show that *American respondents had a slightly higher trust in AI's ability to perform the mechanics of driving, but had less trust in the technology as a whole.*

3.2.5 German Respondent Analysis

For each metric DBA, SDCA, AIT, AIDMT, and DSS, summary statistics including Mean, Standard Deviation, Median, Min and Max were observed and recorded in Table 3.7.

	DBA	SDCA	AIT	AIDMT	DSS
Mean	0.467	0.364	0.459	0.583	0.350
Standard Deviation	0.128	0.164	0.244	0.217	0.122
Median	0.45	0.35	0.411	0.589	0.350
Min	0.1	0.0	0.0	0.062	0.100
Max	0.75	0.85	1.0	1.0	0.675

Table 3.7: German summary statistics.

When considering the German responses, we can observe a clear difference between the DBA and SDCA distributions, as shown in Figure 3.14. Using the Mann-Whitney U test, we captured a p-value of 0.0002 providing statistical evidence of differences between these distributions. This measurement supports the idea that *German drivers prefer a more conservative SDC than their own driving behaviors.* It is also interesting to note that *Germans had the highest mean DBA score across all participants* for this research. Further, the two trust metrics AIT and AIDMT were plotted with the following distribution shown in Figure 3.15.

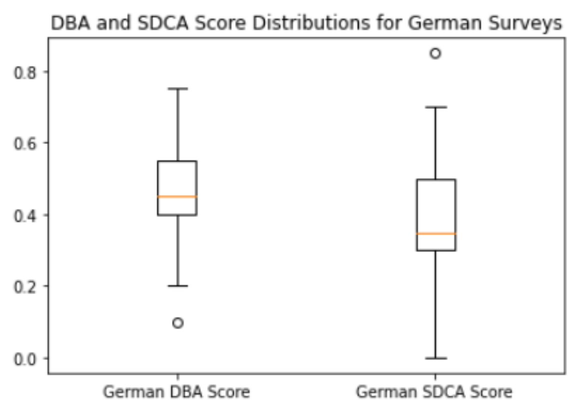

Figure 3.14: German DBA and SDCA score comparison.

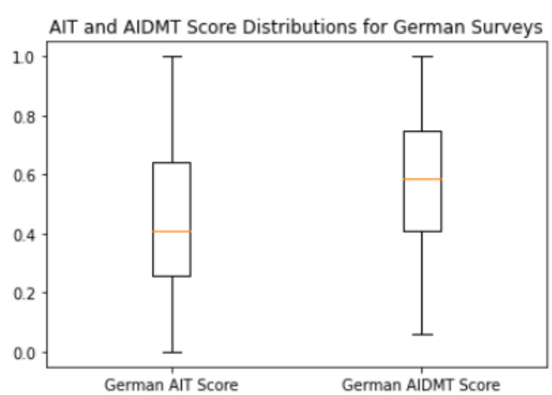

Figure 3.15: German AIT and AIDMT scores.

When considering AI Trust metrics with regards to German respondents, we observed that there exists a slight discrepancy towards general AI trust and trust of AI's ability to perform mechanical driving tasks. While we couldn't find a statistically significant difference between genders for the observed metric among all other participants, we observed statistically significant differences between German males versus females in regards to AIT and AIDMT distributions with a p-value of $2.423E - 05$ and 0.0002, as shown in Figure 3.16, which requires further investigations.

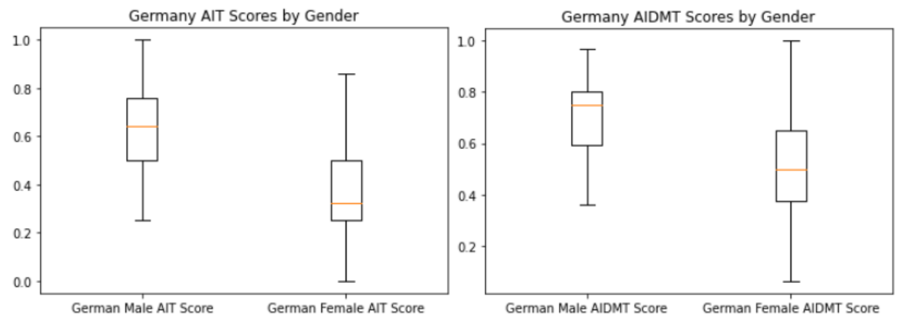

Figure 3.16: German AIT and AIDMT scores by gender.

To note, this discrepancy across genders was only found in the German survey data with all other survey data sets not providing statistically significant differences across genders.

3.2.6 Central American Respondent Analysis

For each metric DBA, SDCA, AIT, AIDMT, and DSS, summary statistics including Mean, Standard Deviation, Median, Min and Max were observed and recorded in Table 3.8.

	DBA	SDCA	AIT	AIDMT	DSS
Mean	0.387	0.249	0.437	0.407	0.194
Standard Deviation	0.132	0.199	0.271	0.279	0.096
Median	0.4	0.25	0.5	0.391	0.200
Min	0.075	0.0	0.0	0.0	0.050
Max	0.75	0.6	1.0	1.0	0.450

Table 3.8: Central American summary statistics.

The Central American responses showed a statistical difference between the DBA and SDCA score with a p-value of 0.003 using the Mann-Whitney U test. This result provides statistical evidence towards *Central American drivers preferring a far more conservative car than their own driving behavior*. These distributions are shown in Figure 3.17. Further, the two trust metrics AIT and AIDMT were plotted with the following distributions shown in Figure 3.18.

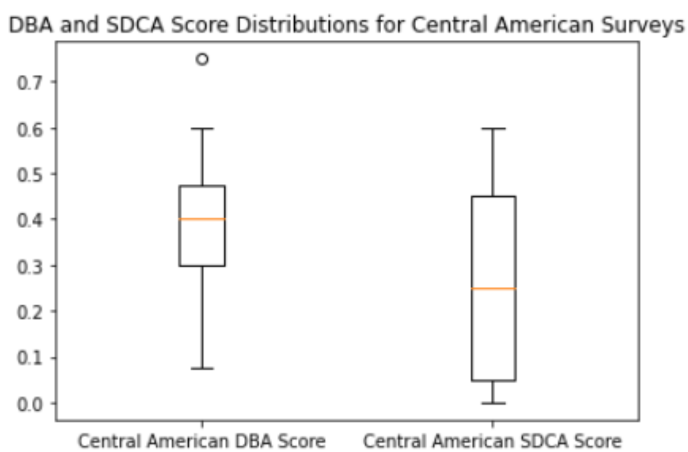

Figure 3.17: Central American DBA and SDCA comparison.

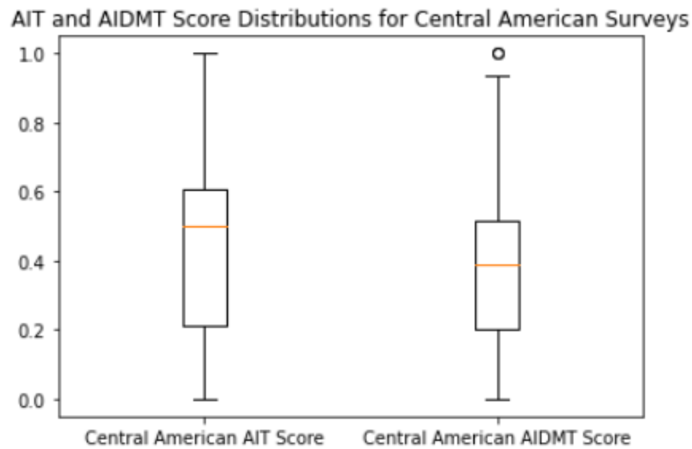

Figure 3.18: Central American AIT and AIDMT scores.

Of note, the *Central American respondents had lower scores in AIT and AIDMT as compared to their American and German counterparts*. It is also noted that Central Americans had more trust in the general nature of AI rather than its ability to perform the mechanics of driving. This is in a sharp contrast to both Americans and Germans who had more trust in AI's ability to manage driving mechanics.

3.2.7 Americans versus Germans

When we compared Americans versus Germans, we found no significant differences in the generated distributions for four of the five metrics SDCA, AIT, and AIDMT. There is evidence to suggest a statistical difference between German DBA scores and American DBA scores with a p-value of 0.0489 as a result of the Mann-Whitney U test. The plots for these distributions can be seen in Figure 3.19. From these, we can interpret that *German drivers have a slightly more aggressive driving style compared to the American drivers*.

3.2.8 Scores across Individual Questions for AI Trust: US and Germany

While aggregate scores yield an overall sentiment for groupings of questions, there's a lot of information to be gained from individual questions. When comparing USA

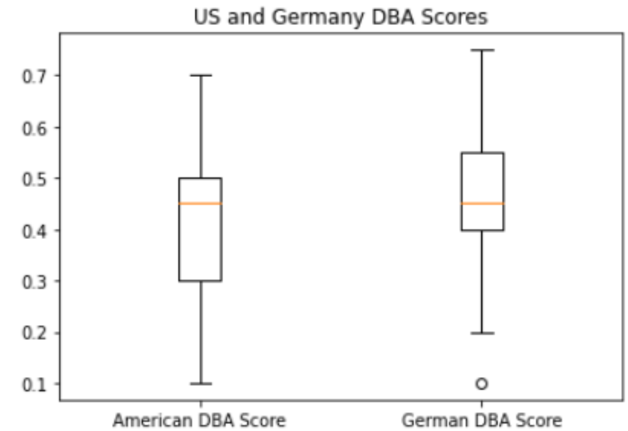

Figure 3.19: Americans and Germans DBA scores.

respondents to German respondents a few questions yielded statistically significant differences in sentiment. In questions relating to AI trust we can see statistical differences in the trust level of using a self driving car when the technology becomes available as well as the trust that said self-driving car will be able to navigate a crowded pedestrian area with p-values of .011 and .009 respectively in a Mann-Whitney U test. This data points to the fact that German respondents were less trusting of self-driving car technology as seen in figure 3.20 and its ability to navigate in crowded areas as seen in figure 3.21. This result was not reflected in the overall AIT statistic as other questions relating to AI trust were generally aligned with the US sentiment.

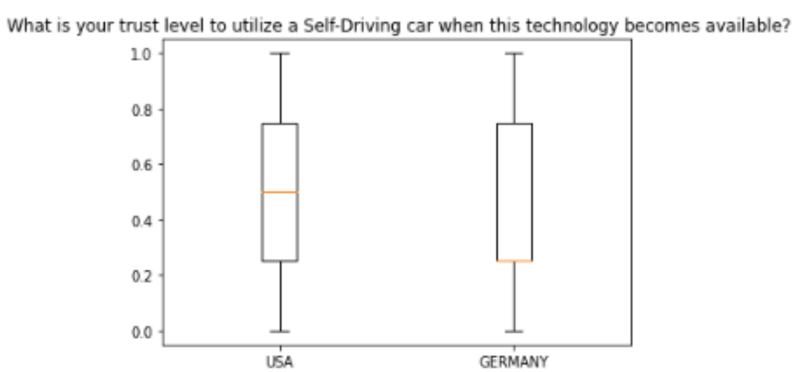

Figure 3.20: Americans and Germans Trust Scores on Self Driving Technology

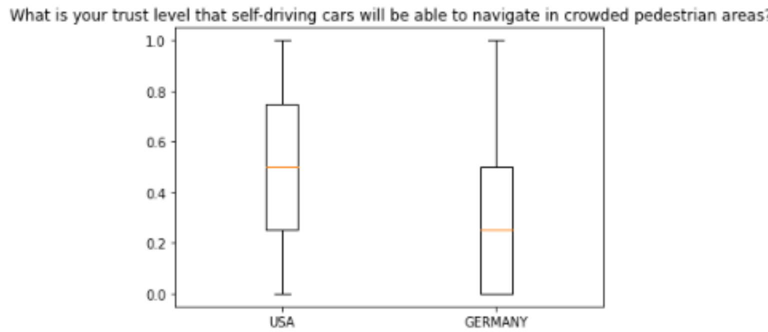

Figure 3.21: Americans and Germans Trust Scores on Navigating Pedestrian Areas

3.2.9 Americans versus Central Americans

When we compared Americans versus Central Americans, we found statistically significant results in the SDCA, AIDMT, and DSS metrics with p-values of 0.003, $5.28E-05$, and $2.84E-08$ respectively. These distributions can be seen in Figure 3.22 and Figure 3.23 The DBA and AIT metrics failed to show any statistically significant differences in these distributions.

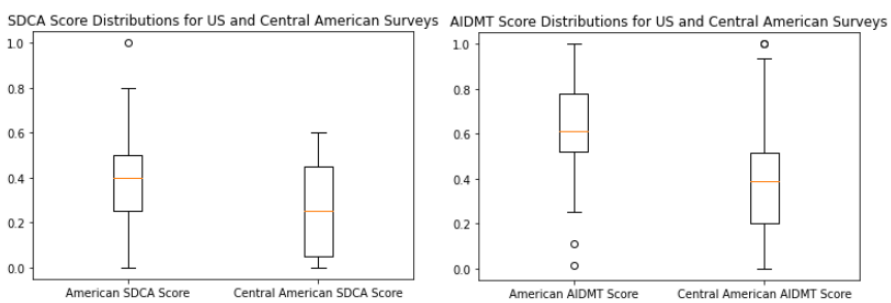

Figure 3.22: Americans and Central Americans SDCA and AIDMT scores.

The differences between SDCA and AIDMT are interesting. The results illustrate that *Central American drivers prefer a more conservative SDC experience relative to the American drivers.* Furthermore, the results show that *Central Americans are less trusting in an AI's ability to perform driving mechanics.* It can also be seen in the lower DSS score that central American drivers tend to take safer driving actions as compared to American drivers.

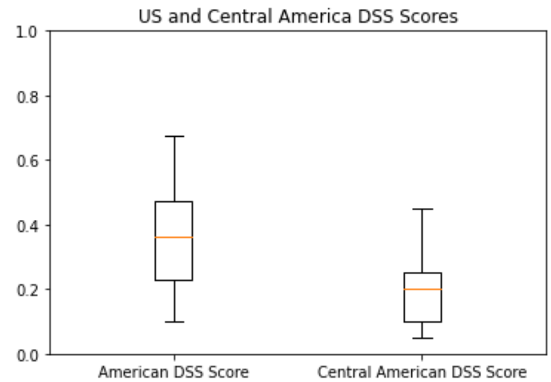

Figure 3.23: Americans and Central Americans DSS score.

3.2.10 Scores across Individual Questions for AI Trust: US and Central America

As seen in the USA vs German AIT score comparison, the aggregate does not fully capture the sentiment across all trust scenarios. When comparing USA sentiment of trust to Central America's trust sentiments for AIT questions we see a few statistical differences in questions relating to safety priority and fully autonomous control with no human intervention. These results showed that American drivers believe that their cars will hold their own safety as an absolute priority compared to Central American drivers. These results also showed that Central American drivers are less likely to trust a Self Driving car to perform without any human component as compared to American drivers. These questions showed statistical differences with p-values of .028 and .0026 respectively in a Mann-Whitney U test. These results can be seen in figure 3.24 and figure 3.25.

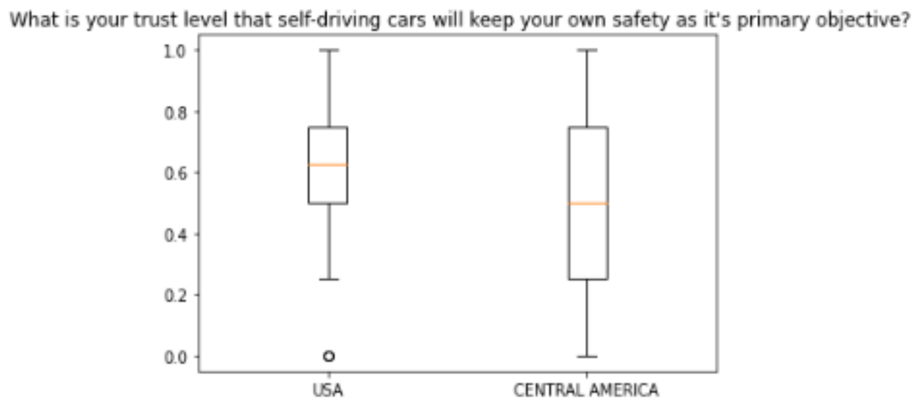

Figure 3.24: Americans and Central Americans Trust Scores on Safety Priority

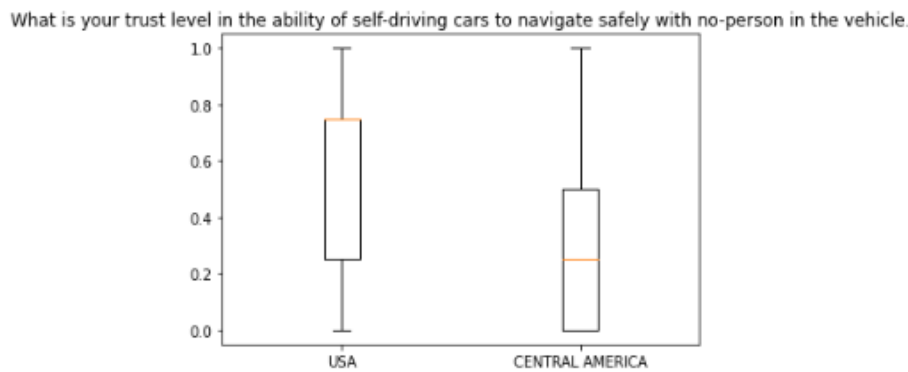

Figure 3.25: Americans and Central Americans Trust Scores on Ability to Perform without Human Intervention

3.2.11 Central Americans versus Germans

When we compared Central Americans versus Germans, we found statistically significant differences in DBA, SDCA, AIDMT, and DSS scores with p-values of 0.003, 0.006, 0.0005, and 2.84E-08 respectively. These distributions can be seen in Figure 3.26, Figure 3.27, and Figure 3.28.

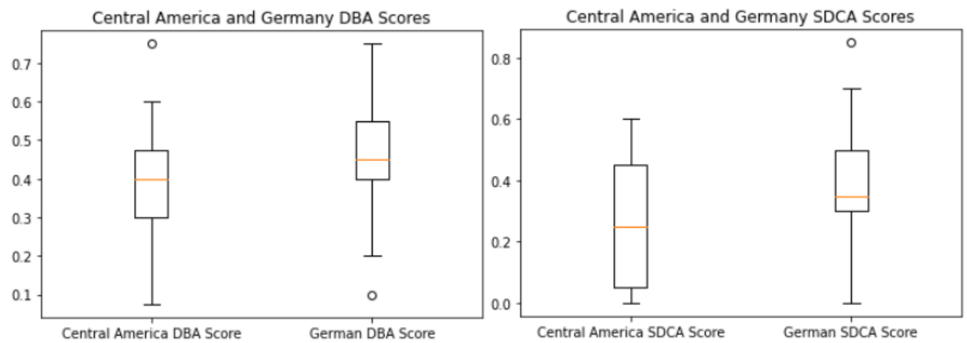

Figure 3.26: Central Americans and Germans DBA and SDCA scores.

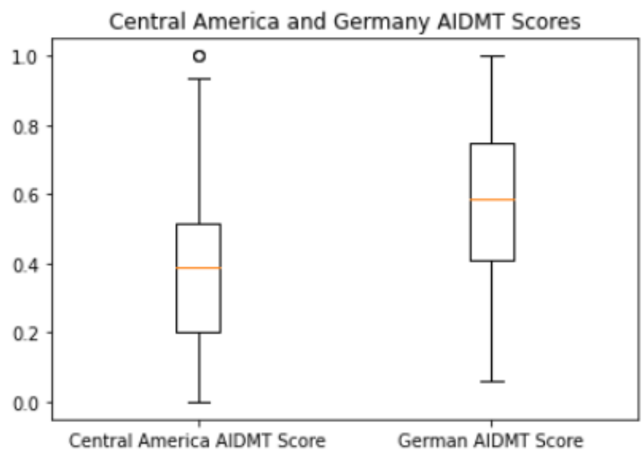

Figure 3.27: Central Americans and Germans AIDMT score.

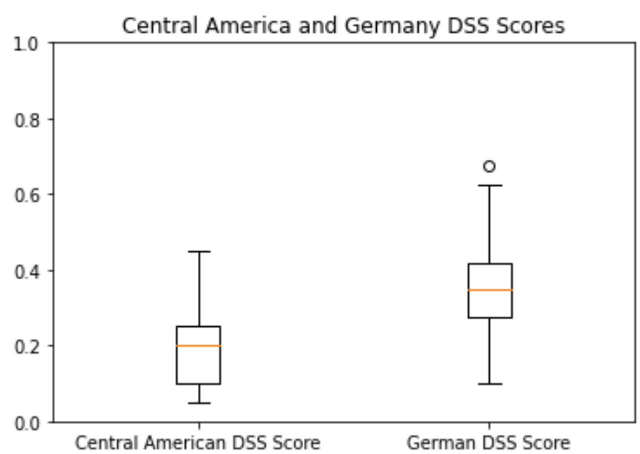

Figure 3.28: Central Americans and Germans DSS score.

From the distributions in Figure 3.26, we can observe that *Central American drivers prefer a more conservative driving style as compared to German drivers*. It is also seen that *Central American drivers expect a more conservative self-driving car compared to German drivers*. There also exists a statistically significant difference in how Central Americans trust the SDC to be able to perform driving mechanics. Figure 3.27 shows that *Central Americans are less trustful in this metric as compared to Germans*. It can also be seen in the lower DSS score illustrated in Figure 3.28 that central American drivers tend to take safer driving actions as compared to German drivers.

3.2.12 Scores across Individual Questions for AI Trust: Germany and Central America

Once again, while overall sentiment of AI trust does not show any statistically significant results, when we consider results between individual questions some stark differences appear. When considering a self driving car's ability to perform in a crowded pedestrian area Central American respondents showed a higher trust level than German respondents, this is verified with a p-value of .047 using a Mann-Whitney U test. Further when considering a self driving car's ability to navigate you to an exact destination we see that German respondents had much larger trust value compared to Central American respondents verfied by a Mann-Whitney U test with a p-value of .01. These results can be seen in figure 3.29 and figure 3.30.

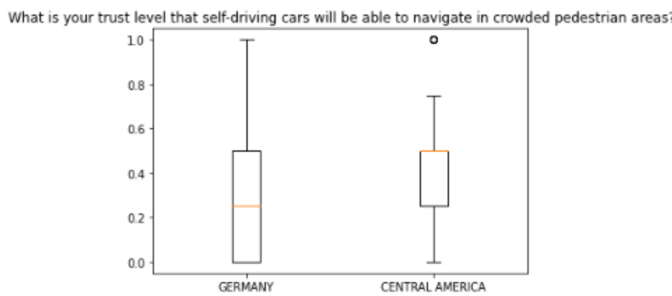

Figure 3.29: Germans and Central Americans Trust Scores on SDC ability to Perform in Crowded areas

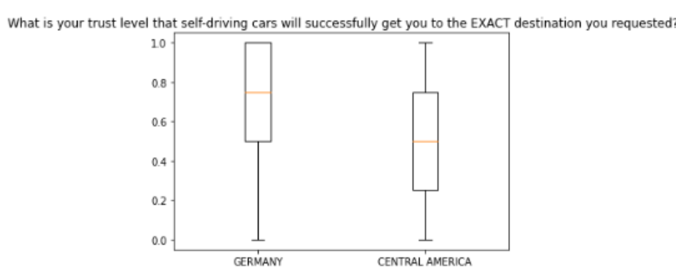

Figure 3.30: Germans and Central Americans Trust Scores on Ability to Navigate to Exact Destinations

3.3 SUBJECTIVE DATA COLLECTION DISCUSSION

There are several takeaways from the research conducted that help yield future considerations when designing autonomous vehicle systems.

3.3.1 Cronbach's Alpha Values

When examining the consistency of our questions we found some interesting results in the measured alpha values. When participants were asked a grouping of questions in the context of their own driving behaviors the corresponding alpha values were low, while if those same questions were asked in the context for a self driving car their alpha values were significantly higher. Likewise, if the context was changed from a highway scenario to a non-highway scenario there would be a significant change in the measured alpha value for a grouping of questions. It was also shown that while one would expect the alpha values of a set of questions to be invariant to the language in which it's asked, there were significant differences between surveyed demographics. These differences show how much context effects a participants view of a particular driving behavior and this context is highly dependent on the experiences they are familiar with based on their own driving experience.

3.3.2 Statistically Significant Measures

The approach taken when examining the survey data was an exploratory approach in which we compare relationships between metrics across demographics. By seeing statistical differences between distributions we can better understand how to serve future passengers in self driving cars. Most metrics between US and German correspondents had similar distributions with the exception of DBA where German drivers had a slightly more aggressive DBA score. The greatest differences were found when comparing both US and German responses to those from Central America. There also existed several statistically significant differences on individual questions related to AI trust and it's ability to perform under various scenarios. These results are summarized in the following list.

- **United States vs German Metrics**

  Similar metric distributions with the exception of DBA where German drivers scored slightly higher.

  US Respondents had a higher trust level in utilizing Self Driving Car technologies when they become available compared to German Respondents.

  US Respondents had a higher level of trust that the self driving car will be able to navigate a crowded pedestrian area compared to German Respondents.

- **United States vs Central American Metrics**

  US Respondents had higher metrics for DBA, SDCA, AIDMT, and DSS scores, but scored similar for the AIT metric.

  US Respondents had a higher trust that the self-driving car will keep its safety as a priority compared to Central American respondents.

  US respondents had a higher trust that the self-driving car will be able to navigate safely with no person in the vehicle compared to Central American respondents.

- **German vs Central American Metrics**

  German Respondents had higher metrics for DBA, SDCA, AIDMT, and DSS scores, but scored similar for the AIT metric.

  Central American had a higher level of trust that the self driving car will be able to navigate a crowded pedestrian area compared to German Respondents

  German respondents had a higher level of trust that the self driving car will be able to navigate to an exact destination compared to Central American respondents.

- **German Men vs German Women AI Trust**

  German Respondents had a statistical difference between genders in both trust metrics AIT, and AIDMT. No other nation demographic showed deviations in any metric across gender.

The potential causes for the observed differences could be a result of several factors. One factor could be the difference in road quality. According to the road quality indicator provided by the World Economic Forum [30] US and German roads score higher than all Central American roads and US and German roads share a similar score of 5.5 and 5.3 respectively. On this scale the highest quality road is Singapore with a score of 6.5. Most The highest scoring Central American country (Panama) scored 4.5 with the average central American country scoring 3.73. One can also consider the digital adoption index (DAI) provided by the World Bank which shows US and Germany having a higher DAI than most Central American countries [31]. The low adoption rate of digital technologies could be one cause of the lower trust observed in AI metrics measured. Overall understanding the proper context driving these differences will be key in delivering autonomous vehicles and AI technology internationally.

3.4 CONCLUDING REMARKS ON SUBJECTIVE DATA COLLECTION

Our research concludes that there exists observable differences in the quantitative metrics defined across the United States, Germany and Central America. Of note, Central America had the lowest average SDCA score that deems a much more conservative SDC experience is requested in that part of the world as compared to both the United States and Germany, which measured a much higher average SDCA score. Furthermore, when comparing Central American respondents to German respondents, statistical differences were found in almost all quantitative measurements suggesting either a vastly different technology should be developed for Central Americans, or a completely different strategy should be employed for social acceptability of SDCs in that region. The data also concluded that there exists a statistically significant difference in the AIT and AIDMT metrics across genders in Germany where women are far less trusting of AI technology and AI's capability to perform driving mechanics. Further the data suggests on individual AI trust questions there exists statistical differences between cultures and their expectations of a self-driving car in various scenarios. Further work on this study can be conducted by expanding the sample size of the nations surveyed as well as increasing the number of nations surveyed to get a better understanding of the global needs of the SDC technology.

CHAPTER 4

DRIVING BEHAVIOR DATA COLLECTION

4.0.1 Mapping Survey Data to User Behaviors

The previous chapter discussed users expectations of self-driving cars through surveyed question data. While these results are interesting and provide insight into cultural expectations they do not provide a clear answer in terms of implementation, only that an adaptive system will be required to adjust behaviors based on expectations. In the field of adaptive self-driving car technologies, there exists several proposed solutions such solutions found in patents provided from Mehrdad Nojoumian [32, 33] suggesting modifying self-driving car behavior based on sensor data from the vehicle and additional sensors. This thesis suggests using survey data to initialize driving behaviors and then using data obtained from smart-phone devices in order to identify and adapt to driving behaviors based on driving observables.

4.0.2 Driving Observables

It can be said that any classical physical system can be represented its velocity and position. When considering a persons driving style we need only consider how the driving style affects the physical observable in the system. How a person turns, breaks, and accelerates are just representations of changing acceleration vectors; therefore, the key to understanding how a person drives is understanding how their acceleration vectors change over time. As such, creating self driving cars that mimic a persons driving behavior begins with collecting data of the persons acceleration data labeled by their driving action.

4.0.3 Data Collection

In order to collect such data let us consider the fact that 85% of Americans now own a smartphone according to a study done by the Pew Research Center in 2021 [34]. One feature of the vast majority of smartphones is the rich sensor set embedded into the technology. Of interest accelerometer, gyroscopes, and GPS sensors allow for the rough calculation of any physical observable in regards to driving behavior. These observables will be measured with respect to the device in the default position as shown in 4.1.

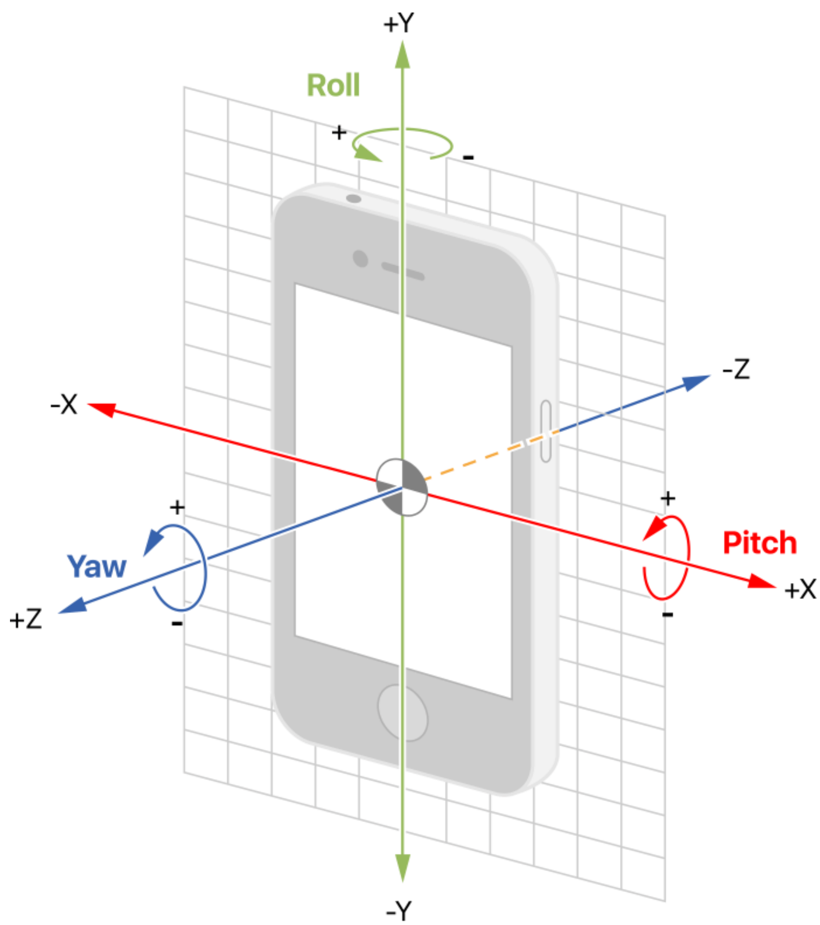

Figure 4.1: iPhone Reference Frame [6]

This thesis proposes a cloud-based architecture in order to collect data at scale in order to generate driving profiles based on driving behaviors. At a high level users will interact with AWS API Gateway through post requests, these requests are parsed through AWS Lambda and then stored into a NoSQL database DynamoDB. Data from dynamo DB is then inferred using AWS Sagemaker and results stored into a S3 bucket. This data can then be formatted for user viewing via AWS Quicksight. A high level diagram of this process can be seen in figure 4.2. The design presented

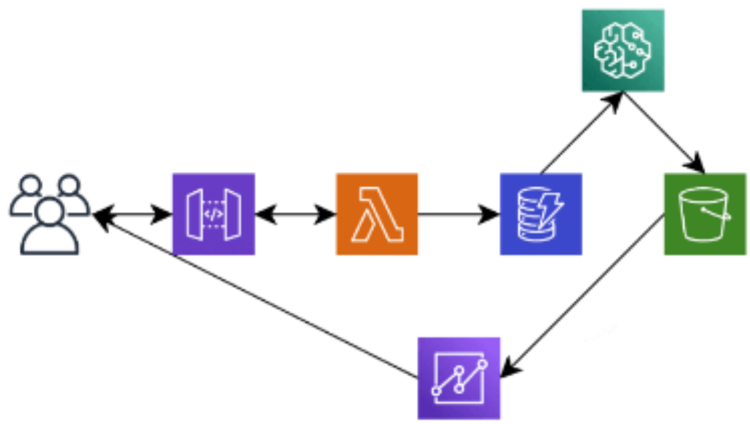

Figure 4.2: AWS Cloud Based Architecture Diagram

provides several unique advantages. The main advantage is that this system can be rapidly scaled and ported. As we are using an API based infrastructure any device with the correct sensors and an internet connection can be incorporated into this framework.

4.0.4 Application Proof of Concept

The framework discussed in the previous section was built as a proof of concept and turned into an iOS application for recording data. Data can be labeled for specific behaviors to be captured. The proof of concept for this application is shown in figure 4.3.

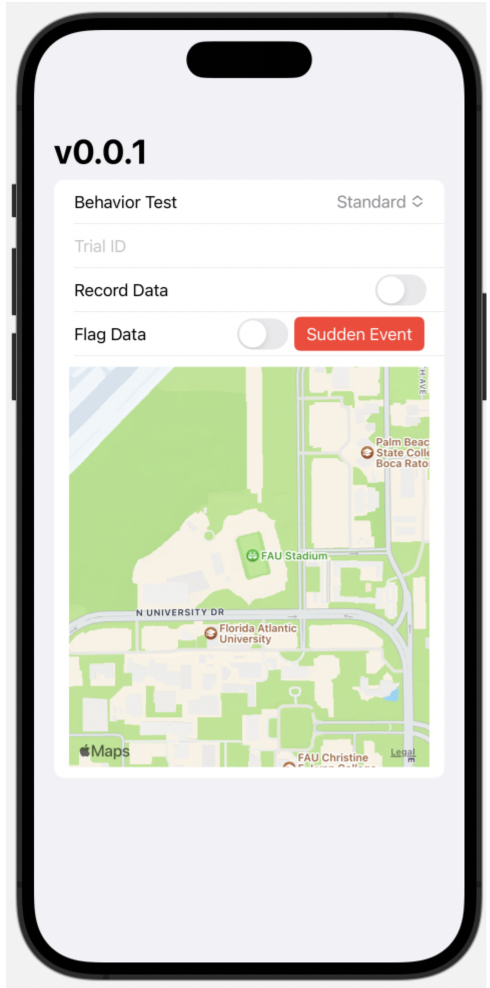

Figure 4.3: Data Collection Application Proof of Concept

This application currently requires two users to be used safely and effectively where one user is the driver and the second user is the data recorder. The driver and data collector will first agree on a test to be conducted and a trial id to refer back to the given trial. Once the experiment is ready to be conducted the data recorder will toggle the record data button. When recording data the gyroscopes, accelerometers, and GPS sensors outputs will be gathered and bundled into a post request to the AWS endpoint at a frequency of 1Hz. The data recorder can label data on the fly through the use of the flag data toggle. Sudden unexpected events while driving can be flagged with the sudden event button which which will flag the timestamp with the sudden event when recording data. A sample of the resulting table populated in AWS can be see in figure 4.4.

device_id	timestamp	acc_x	acc_y	acc_z	event	latitude	longitude	pitch	roll	test_name	trial_id	yaw
59D45CB2-537B-4D8...	1664547093	0.1380214...	0.0092000...	-0.0648861...	0	26.350875...	26.350875...	1.4018492...	-0.2294582...	standard	99	1.6109826086125867
59D45CB2-537B-4D8...	1664547094	-0.0072090...	0.0459149...	-0.1824138...	0	26.350875...	26.350875...	1.3994294...	-0.2252904...	standard	99	1.828797963135238
59D45CB2-537B-4D8...	1664547095	0.2393718...	0.1669195...	-0.0984616...	0	26.350875...	26.350875...	1.3998027...	-0.2376637...	standard	99	2.120073481519116
59D45CB2-537B-4D8...	1664547096	0.2199480...	0.0491709...	-0.1087199...	0	26.350875...	26.350875...	1.4051969...	-0.2429160...	standard	99	2.4634464324205037
59D45CB2-537B-4D8...	1664547097	0.1411574...	0.0813462...	-0.1109151...	0	26.350875...	26.350875...	1.4004197...	-0.2773864...	standard	99	2.871861231057183
59D45CB2-537B-4D8...	1664547098	0.1458217...	-0.0296933...	0.0639996...	0	26.350875...	26.350875...	1.3996035...	-0.3088465...	standard	99	-3.000403114557065
59D45CB2-537B-4D8...	1664547099	-0.0656883...	-0.1148719...	-0.1207763...	0	26.350875...	26.350875...	1.4040254...	-0.3633105...	standard	99	-2.7817022921361527
59D45CB2-537B-4D8...	1664547100	-0.0344379...	0.0262704...	0.0489873...	0	26.350875...	26.350875...	1.3941921...	-0.4074028...	standard	99	-2.696251061350724
59D45CB2-537B-4D8...	1664547101	-0.0117147...	-0.0410746...	0.0348434...	0	26.350875...	26.350875...	1.3953654...	-0.3917619...	standard	99	-2.7109945904757247
59D45CB2-537B-4D8...	1664547102	0.0718983...	0.0975057...	-0.1294262...	0	26.350875...	26.350875...	1.3988094...	-0.3515247...	standard	99	-2.7500372618945583
59D45CB2-537B-4D8...	1664547103	0.0277798...	-0.0570839...	-0.1278669...	0	26.350875...	26.350875...	1.3981696...	-0.3570579...	standard	99	-2.74459239290534

Figure 4.4: DynamoDB NoSQL Table

As the data is being added in real-time we can perform analytics on the stream as data comes in. Future research can consider adapting self-driving car behavior based on historical observables from a given users driving profile. For example how hard a user likes to take a turn and how they tend to break are inherently encoded into the accelerometer data and can be used as a training set for turning and braking models. An example of raw data extracted from the sensors can be seen in figure 4.5. In this frame a positive G-Force value in Z represents braking while negative result represents accelerating. Likewise positive x g-forces represents a left turn of the vehicle and negative x g-forces represents a right turn of the vehicle. The raw values however have a lot of noise and make observing behaviors difficult. In order to provide a more interpretable result we consider an exponential moving average calculated with a span of 60 which weights the measured values heavily to more recent values. This result can be see in figure 4.6. In the exponential moving average graph we can see diversions between acceleration in z and x showing how a driver reacts to a turn by either speeding into the turn or breaking into the turn. Measures such as these can play a key role in modeling driving behaviors.

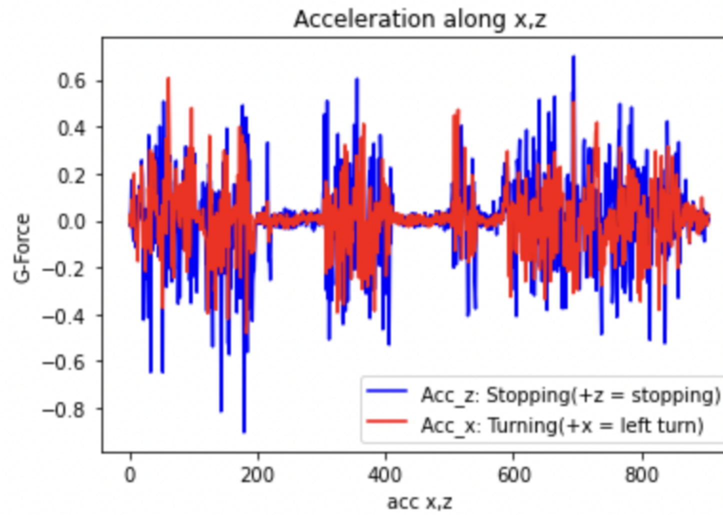

Figure 4.5: Raw Accelerometer Data in X, Z axis

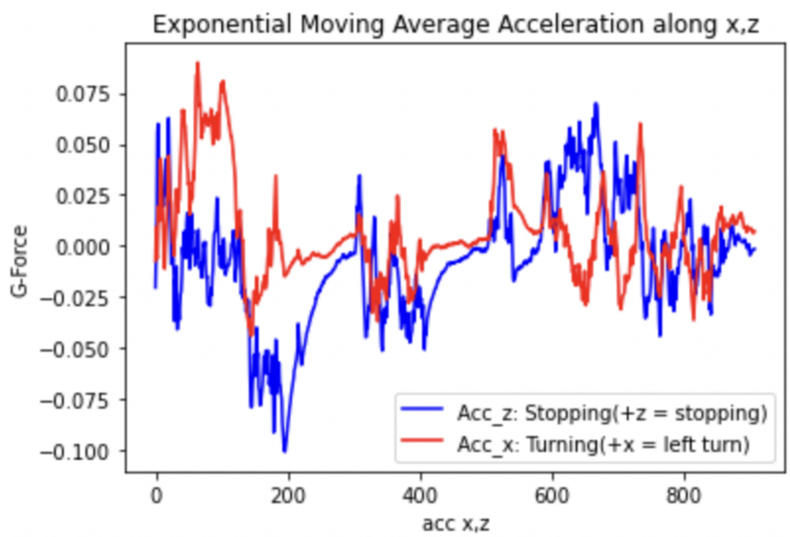

Figure 4.6: Exponential Moving Average Accelerometer Data in X, Z axis

In addition to driver behavior modeling several secondary benefits can be enjoyed while employing this system. As data is processed in real-time additional safety systems such as crash detection and behavior prior to crash can be identified. Further dangerous driving behaviors can be detected and alert a driver to improve based on recorded observations in the form of a personalized driving dashboard which describes the dangerous behaviors to the driver.

CHAPTER 5

CONCLUSIONS

This thesis explores the cross-cultural expectations of self-driving cars based on an international survey. The data analysis suggested several statistical differences between surveys distributed to different international respondents. The results suggest that strategies used for deploying self driving cars for mass adoption in different countries has to be tuned to the sentiments of said countries in order to match their standards of trust, safety, and comfort. Further this thesis provides a highly scalable method of data collection in order to capture driving behaviors without the need of obtrusive sensors and complex installations in the vehicle. It is a matter of future research to be able to tie the driving usage behavior data to the surveyed driving response.

BIBLIOGRAPHY

[1] N. B. Geddes, *Magic motorways / Norman Bel Geddes.* Random House [New York], 1940.

[2] D. Pomerleau, "Alvinn: An autonomous land vehicle in a neural network," in *Proceedings of (NeurIPS) Neural Information Processing Systems* (D. Touretzky, ed.), pp. 305 – 313, Morgan Kaufmann, December 1989.

[3] J. Redmon, S. K. Divvala, R. B. Girshick, and A. Farhadi, "You only look once: Unified, real-time object detection," *CoRR*, vol. abs/1506.02640, 2015.

[4] Society of Automotive Engineers, "Sae international releases updated visual chart for its "levels of driving automation" standard for self-driving vehicles." `https://www.sae.org/news/press-room/2018/12/sae-international-releases-updated-visual-chart-for-its-%E2%80%9Clevels-of-driving-automation%E2%80%9D-standard-for-self-driving-vehicles`. Accessed: 2022-11-25.

[5] J. Craig and M. Nojoumian, "Should self-driving cars mimic human driving behaviors?," in *3rd International Conference on HCI in Mobility, Transport and Automotive Systems (MobiTAS)*, LNCS 12791, pp. 213–225, Springer, 2021.

[6] Apple, "Understanding reference frames and device attitude." `https://developer.apple.com/documentation/coremotion/getting_processed_device-motion_data/understanding_reference_frames_and_device_attitude`. Accessed: 2022-11-20.

[7] C. Teale, "Amid tesla's autopilot probe, nearly half the public thinks autonomous vehicles are less safe than normal cars," SEPT 2021.

[8] F. Hartwich, C. Hollander, D. Johannmeyer, and J. F. Krems, "Improving passenger experience and trust in automated vehicles through user-adaptive hmis:"the more the better" does not apply to everyone," *Frontiers in Human Dynamics*, p. 38, 2021.

[9] F. Hartwich, C. Witzlack, M. Beggiato, and J. F. Krems, "The first impression counts–a combined driving simulator and test track study on the development of trust and acceptance of highly automated driving," *Transportation research part F: traffic psychology and behaviour*, vol. 65, pp. 522–535, 2019.

[10] S. Shahrdar, C. Park, and M. Nojoumian, "Human trust measurement using an immersive virtual reality autonomous vehicle simulator," in *2nd AAAI/ACM Conference on Artificial Intelligence, Ethics, and Society (AIES)*, pp. 515–520, ACM, 2019.

[11] S. Shahrdar, L. Menezes, and M. Nojoumian, "A survey on trust in autonomous systems," in *Intelligent Computing* (K. Arai, S. Kapoor, and R. Bhatia, eds.), (Cham), pp. 368–386, Springer International Publishing, 2019.

[12] S. Ittner, D. Mühlbacher, and T. H. Weisswange, "The discomfort of riding shotgun–why many people don't like to be co-driver," *Frontiers in Psychology*, vol. 11, p. 584309, 2020.

[13] K. Mühl, C. Strauch, C. Grabmaier, S. Reithinger, A. Huckauf, and M. Baumann, "Get ready for being chauffeured: Passenger's preferences and trust while being driven by human and automation," *Human factors*, vol. 62, no. 8, pp. 1322–1338, 2020.

[14] C. Basu, Q. Yang, D. Hungerman, M. Singhal, and A. D. Dragan, "Do you want your autonomous car to drive like you?," in *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction*, pp. 417–425, 2017.

[15] C. Park and M. Nojoumian, "Social acceptability of autonomous vehicles: Unveiling correlation of passenger trust and emotional response," in *4th International Conference on HCI in Mobility, Transport and Automotive Systems (MobiTAS)*, LNCS 13335, pp. 402–415, Springer, 2022.

[16] Deloitte, "2020 global automotive consumer survey." `https://www2.deloitte.com/content/dam/Deloitte/ca/Documents/consumer-industrial-products/Global_Automotive_Consumer_Study_EN_Web_AODA.pdf`. Accessed: 2022-08-15.

[17] K. Bimbraw, "Autonomous cars: Past, present and future - a review of the developments in the last century, the present scenario and the expected future of autonomous vehicle technology," *ICINCO 2015 - 12th International Conference on Informatics in Control, Automation and Robotics, Proceedings*, vol. 1, pp. 191–198, 01 2015.

[18] K. Dowling, R. Guzikowski, J. Ladd, H. Pangels, S. Singh, and W. R. L. Whittaker, "Navlab: An autonomous navigation testbed," Tech. Rep. CMU-RI-TR-87-24, Carnegie Mellon University, Pittsburgh, PA, November 1987.

[19] E. Dickmanns, R. Behringer, D. Dickmanns, T. Hildebrandt, M. Maurer, F. Thomanek, and J. Schiehlen, "The seeing passenger car 'vamors-p'," in *Proceedings of the Intelligent Vehicles '94 Symposium*, pp. 68–73, 1994.

[20] C. Thorpe, M. Hebert, T. Kanade, and S. Shafer, "Vision and navigation for the carnegie-mellon navlab," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 10, no. 3, pp. 362–373, 1988.

[21] S. Thrun, M. Montemerlo, H. Dahlkamp, D. Stavens, A. Aron, J. Diebel, P. Fong, J. Gale, M. Halpenny, G. Hoffmann, K. Lau, C. Oakley, M. Palatucci, V. Pratt, P. Stang, S. Strohband, C. Dupont, L.-E. Jendrossek, C. Koelen, C. Markey, C. Rummel, J. van Niekerk, E. Jensen, P. Alessandrini, G. Bradski, B. Davies, S. Ettinger, A. Kaehler, A. Nefian, and P. Mahoney, *Stanley: The Robot That Won the DARPA Grand Challenge*, pp. 1–43. Berlin, Heidelberg: Springer Berlin Heidelberg, 2007.

[22] S. Verghese, "Self-driving cars and lidar," in *2017 Conference on Lasers and Electro-Optics (CLEO)*, pp. 1–1, 2017.

[23] Tesla, "Tesla vision update: Replacing ultrasonic sensors with tesla vision." `https://www.tesla.com/support/transitioning-tesla-vision`. Accessed: 2022-09-13.

[24] B. Williams, *Automated Driving Levels*, pp. 19–41. 2021.

[25] Nature, "Safe driving cars," *Nature Machine Intelligence*, vol. 4, pp. 95–96. Accessed: 2022-09-13.

[26] E. Awad, S. Levine, M. Kleiman-Weiner, S. Dsouza, J. Tenenbaum, A. Shariff, J.-F. Bonnefon, and I. Rahwan, "Drivers are blamed more than their automated cars when both make mistakes," 02 2020.

[27] J.-F. Bonnefon, A. Shariff, and I. Rahwan, "The social dilemma of autonomous vehicles," *Science*, vol. 352, no. 6293, pp. 1573–1576, 2016.

[28] A. Shariff, J.-F. Bonnefon, and I. Rahwan, "Psychological roadblocks to the adoption of self-driving vehicles," *Nature Human Behaviour*, vol. 1, 09 2017.

[29] S. Kolekar, J. de Winter, and D. Abbink, "Human-like driving behaviour emerges from a risk-based driver model," *Nature Communications*, vol. 11, no. 1, 2020.

[30] K. Schwab, "The global competitiveness report 2019." `http://www3.weforum.org/docs/WEF_TheGlobalCompetitivenessReport2019.pdf`. Accessed: 2022-08-15.

[31] International Bank for Reconstruction and Development, *World Development Report 2016: Digital Dividends*. World Bank, 2016.

[32] M. Nojoumian, "Adaptive driving mode in semi or fully autonomous vehicles," 2022. US Patent 11,221,623.

[33] M. Nojoumian, "Adaptive mood control in semi or fully autonomous vehicles," 2021. US Patent 10,981,563.

[34] A. Perrin, "Mobile technology and home broadband 2021." `https://www.pewresearch.org/internet/2021/06/03/mobile-technology-and-home-broadband-2021/`. Accessed: 2022-09-13.