The Effect of an Educational Intervention on Affect and

Trust of Autonomous Vehicles

by

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ABSTRACT

With the growth of autonomous vehicles' prevalence, it is important to understand the relationship between autonomous vehicles and the other drivers around them. More specifically, how does one's knowledge about autonomous vehicles (AV) affect positive and negative affect towards driving in their presence? Furthermore, how does trust of autonomous vehicles correlate with those emotions? These questions were addressed by conducting a survey to measure participant's positive affect, negative affect, and trust when driving in the presence of autonomous vehicles. Participants' were issued a pretest measuring existing knowledge of autonomous vehicles, followed by measures of affect and trust. After completing this pre-test portion of the study, participants were given information about how autonomous vehicles work, and were then presented with a posttest identical to the pretest. The educational intervention had no effect on positive or negative affect, though there was a positive relationship between positive affect and trust and a negative relationship between negative affect and trust. These findings will be used to inform future research endeavors researching trust and autonomous vehicles using a test bed developed at Arizona State University. This test bed allows for researchers to examine the behavior of multiple participants at the same time and include autonomous vehicles in studies.

TABLE OF CONTENTS

CHAPTER 1

INTRODUCTION

In 2016, Arizona had 126,845 car accidents killing 962 people (Arizona Department of Transportation Crash Facts 2016). What can be done to overcome this serious problem? One approach is to remove the human from the driver's seat, allowing the car to operate itself. Autonomous vehicles (AV) are a rapidly growing technology that will change the way people travel; by allowing people who are disabled to travel and work to be done while in transit. However, it will be years before every car on the road will be autonomous. This leaves us with a mixed environment of vehicles with varying levels of autonomy, including technology that ranges from helping drivers back up the vehicle to fully driving the vehicle for them.

The current study uses an exploratory survey to address the effect of knowledge about autonomous vehicles on emotional response to those vehicles. Research conducted by Dingus, Guo, Lee, et al (2016) found that drivers with an elevated emotional state were 9.8 times more likely to get into a car accident. The issue of how AVs would affect drivers' emotional state is important to address due to how rapidly the autonomous vehicle field is growing. The goal of this type of research is to avoid some of the cited issues above and any other unknown effects that could exist.

This thesis addresses how presenting participants with information about AVs affects their positive and negative affect towards driving while in the presence of AVs. It also addresses how trust of autonomous vehicles correlates with affect. Research by Ososky et al (2013) states that for users to have appropriate trust of autonomy they must understand its capabilities and limitations. Because of this it is hypothesized that the educational information about autonomous vehicles will induce negative emotions in participants, with trust correlating in a positive direction with affect. This negative effect is expected because the current capabilities of autonomous vehicles are not as robust as one would expect and the lack of a public understanding of how AVs work.

CHAPTER 3

BACKGROUND

Emotion and Driving. Poó and Ledesema (2013) conducted research that was focused on driving styles and how they relate to personality. They believed that personality traits would be embodied in the driving styles of individuals. The researchers collected data from 908 Argentine drivers by using the Multidimensional Driving Style Inventory (MDSI, Taubman-Ben-Ari et al 2004) and the Zuckerman-Kuhlman Personality Questionnaire. The authors found positive correlations between impulsive personality traits and risky, angry, and dissociative driving styles. The dissociative driving style is categorized by Taubman (2004) as someone who tends to be easily distracted while driving and then makes mistakes because of that distraction. There were also strong correlations between aggression-hostility traits and risky and angry driving styles and between neuroticism-anxiety traits and dissociative driving style. Furthermore, there was only one negative correlation found between careful driving styles and the impulsive and aggressive personality traits.   Overall Poo and Ledesma found was that personality traits can be used to predict someone's driving style. This finding culd allow researchers to be able to extrapolate the type of effect a change in emotion could have on someone's driving behavior. For example, we could say that someone who is easily distracted could see an autonomous vehicle and lose focus on their task at hand. The World Health Organization lists distraction as one of the major risk factors for road traffic injuries, stating that being distracted by a mobile phone makes a driver 4x as likely to be in an accident (WHO, 2016). Therefore, if autonomous vehicles turn out to be more of a distraction or just another thing to be mad at on the road then they will be more of a hazard than a helpful tool. This finding is also relevant because it implies that well designed autonomous vehicles will affect people differently from person to person based on their personality, and it important to design vehicles that would take this into account.

Another study looked directly at the way mood can affect driving. Hu et al., (2013) conducted research to see how mood and emotion would affect how people drive. This was done by presenting either positive or negative stimuli before having participants complete driving related tasks. The independent variable was the initial stimuli presented to participants in the form of positive or negative videos and the dependent variable was the person's driving behavior after the stimuli was presented. The authors hypothesized that the negative videos would increase danger perception while driving on the road, and found this hypothesis to be supported. Hu et al. (2013) found that participants who watched the negative video experienced negative emotions and had a higher perception of danger on the road than those with the positive affect. However, this higher perception also came with riskier driving behavior. This same reaction may also be found with exposure to autonomous vehicles. The Hu et al., (2013) paper points out that negative affect destroys driver's decision making and that drivers are more likely to consider risky driving acceptable. If the autonomous vehicles behave in unfavorable ways to drivers or if the drivers have seen negative news coverage; then negative emotions could result leading to riskier driving behaviors that could lead to traffic accidents or road rage incidents. These findings point out that people's emotional states may affect the way that they drive on the road, which gives researchers more reason to consider this fact early in the autonomous vehicle's design.

A meta-analysis of the association between anger and aggressive drivin*g* that involved 51 studies was conducted by Raluca Bogdan, Ma, and Havârneanu (2016). The authors tested four different hypotheses related to anger. The first stated that there is a positive relation between anger and aggressive driving. They defined aggressive driving as verbal aggression, physical signaling, and types of driving behavior that would require the police to get involved such as being involved in an accident. The results indicated that anger does have a positive association with aggressive driving. The authors also compared general anger to specific driving anger. The difference between the two is that general anger is all encompassing anger whereas driving anger comes specifically from driving. What they found is that general anger had a larger effect on aggressive driving than specific driving anger, which would mean people who were already angry when they start driving would drive more aggressively. The authors also completed analyses based on age, gender, region and driving experience. These analyses showed that women were more likely to show verbal aggression, whereas less experienced drivers were prone to aggressive driving behavior. These results from this meta analyses, like the results from Hu et al. (2013)., provide additional support that emotions can and will affect driving in unpredictable and possibly dangerous ways.

Despite negative emotions perhaps being the obvious culprit in poor driving performance and likely car accidents it has been found by several studies that positive emotions also degrade driving skills. Jeon, Walker, and Yim (2014) conducted a study in which 70 undergraduate students drove in a driving simulator with induced anger, fear, happiness, or neutral emotional states. Risk perception, driver confidence, and safety level were subjectively assessed. Then the authors looked at four types of driving errors while participants operated the simulator; specifically, lane keeping, traffic rules, aggressive driving, and collision while driving. Anger and happiness both showed degraded driving performance compared to the neutral and fear conditions. In another study conducted by Rhodes and Pivik (2011), researchers conducted a phone survey that collected data from 504 teens (16-20) and 409 adults (25-45). Researchers found that risk perception and positive affect were both independent predictors for driving behavior. Positive affect specifically was found to be a stronger influence on male and teen drivers than female and adult drivers. This indicates that positive affect can affect driving behavior and paired with the work of Jeon, Walker, and Yim (2014), could be a factor that also predicts riskier driving.

Cai, Lin, and Mourant (2007) used a novel simulation design to study driving interactions between humans that used research assistants to drive other vehicles in the study. The participants were placed in a high-fidelity driving simulator and then used research assistants with low fidelity simulators to drive within the same environment. The researchers' first aim was to determine if realistic interactions between vehicles and humans could be achieved by replacing driver models with actual human drivers. Their second goal was to see how driver emotion affected their performance using the new system simulator system. Before the participants were asked to run through the protocols they were asked to watch either a neutral, exciting, or an angering activity depending on the conditions they were placed. The researchers then used physiological measures to determine the emotional state of the participants, including heart rate and skin conductance. They then compared that data with driving performance found in angry or excited states. After this comparison participants in the angry or excited condition were found to have poorer driving performance than those in the calm condition. This priming effect is an important aspect for the current study, as it displays that driving in an elevated emotional state can impact driving performance.

The above literature sets the ground work that emotion is an important factor that affects driving behavior and should be considered while designing autonomous cars. The effects of these driverless vehicles on human drivers has yet to be seen or studied. This suggests that autonomous vehicles should avoid inciting emotions in drivers.

Trust is a crucial element for human to human interaction, and the same is true of human to automation interaction. Lee and See examined several definitions of trust that have been put forth by other papers and then defined trust in automation as, "…the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee and See, 2004). The authors also continued to define important concepts for measuring mismatches in trust and the capabilities of autonomy. Keeping these mismatches in mind it is important for companies to consider these issues while creating autonomous vehicles. Developing the proper amount of trust from users requires the correct calibration, resolution, and specificity (Lee & See, 2004). Calibration refers to whether a user's trust of autonomy matches its capabilities. For example, poor calibration would be reflected in a case in which someone over trusted a machine to do a whole job when its capabilities were suitable for half the job. This is what has occurred in many of the reported fatal Tesla accidents. Another way to describe this would be appropriate trust, like that described by Ososky et al (2013) which comes from building an accurate mental model of a systems capabilities. Distrust on the other hand would have users not maximizing the potential help that the autonomy could bring. Resolution is similar to calibration, however it looks at the range of possible capabilities and whether they map on to a range of trust. Issues with resolution occur when autonomy has a broad range of capabilities that maps onto a small range of trust. When changes occur in a piece of autonomy's capabilities and they are met with minor changes in trust, this also represents bad resolution of trust with autonomy. An example of a resolution problem is only trusting a vehicle's backup camera and lane assist capabilities when the vehicle is capable of autonomous driving. The last mismatch of trust with autonomy is specificity, which refers to the trust of a specific component of a machine/computer's autonomy. An example of a specificity mismatch while driving an autonomous vehicle would be trusting the vehicle's adaptive cruise control, which modifies cruising speed based on the distance of the next car on the road, but not trusting the vehicles lane assist. In this scenario the operator is trusting one form of the vehicles autonomy, but not trusting another system. These findings are important to consider when it comes to understanding trust and autonomy, not only in a static environment, but also in a dynamic one with multiple forms of autonomy operating at once.

Hancock et al. (2011) conducted a meta-analysis on human robot interaction (HRI) and trust. They found that there was a moderate global effect for all the factors they researched including the environment, humans, and robot-related factors. However, they did find that the environmental and human related factors were not as strongly related to trust development as the other factors. Robot related factors were found to be moderately related as well, but robot performance was strongly related to trust. This makes sense because if a piece of machinery breaks, humans are less likely to trust it in the future. Researchers also found that robot attributes had a relatively small role in human trust of the robot. One question raised by this research is how much an AV's performance can break down before participant trust of the machine begins to break down.

Another study, looking specifically at how human-automation trust can be affected by automation errors was conducted by Madhaven, Wiegmann, and Lacson (2006). Researchers used a target detection task that incorporated an autonomous decision aid. In Study 1 a decision aid missed a target on either easy trial or in difficult trials. In their second study the researchers added another kind of error the aid could make, false alarms, in addition to the easy or difficult targets. This research found that errors on tasks that the human operator deems "easy" degraded trust and reliance on the automation. The authors suggested that automation designers should do their best to design automation that avoids easy errors or actively tries to circumvent the negative effects that errors bring.

Trusting automation is an important feature in human- automation interaction. For autonomous vehicles to be implemented in a way that maximizes benefits, users will need to trust them with their lives. Designing for trust that is properly calibrated for autonomous vehicles is imperative to acquire the benefits in safety that automation is meant to help solve on the roadways. If trust does covary with affect it would be an important variable to consider while designing automation that does not overly elevate drivers' emotions. Emotions like anger or happiness have been shown to affect driving behavior in previously reviewed literature, and it is expected that trust correlates positively with affect. For example, if someone has high positive affect you would expect for them to have higher levels of trust and vice versa for negative affect.

Perception of Autonomous Vehicles

One last key component for how AVs will interact with other drivers is how the autonomous vehicle is perceived. This is an important consideration because of people's natural tendency to build biases either for or against any type of technology. In a survey conducted by Hulse, Xie, and Galea (2018); researchers found that AVs were relatively safe when compared to motorcycles and bicycles. However, trains, both autonomous and human operated, were rated to be safer than AVs. Hulse, Xie, and Galea also found that pedestrians crossing the road rated autonomous vehicles as safer than their human operated counterparts. These finding revealed a general sense of trust for autonomous vehicles.

The user's willingness to pay for these technologies will be an important factor to consider while designing automation. In a survey, Bansel and Kockelman (2018) surveyed 1088 people from across the state of Texas about their opinions on smart vehicles and other connected vehicles. In this survey they found that older and more experienced drivers were less willing to pay for AVs or connected autonomous vehicles (CAV). They also found that higher income and more safety-oriented people are more likely to pay for connectivity and autonomy. Other findings found that 53.9% of respondents believe AVs would help fuel economy and that 53.1% of respondents believe that AVs would decrease the number of accidents. Although these numbers only represent roughly half of the respondent population, these results are significant, given that AVs have just recently entered the spotlight in the last couple years.

The public perception of autonomous vehicles likely impacts the trust that users would have of AVs before ever interacting with autonomous vehicle. Also, the reviewed perceptions likely feed into how much people trust autonomous vehicles. It is important for people to have the right perception of autonomous vehicles, if they are presented with too much negative information in the news then an availability bias might develop, especially because the spotlight tends to shine on AVs the most after some terrible accident.

Education on AVs and Calibration of Trust

Defining calibration is important to understanding the interaction between autonomy and trust. Lee and See (2004) defined it as the alignment of a user's trust in a system and the performance capabilities of an autonomous agent. Calibration can be operationalized in three ways as perceptual accuracy, perceptual sensitivity, and trust sensitivity (Merrit 2014). In Merrit's 2014 study only perceptual accuracy, which is defined as the extent to which user's perception of reliability reflects the actual reliability was shown to be significantly associated with task performance or the ability to identify failures. The importance of accurate assessment of reliability implies that an understanding of the AV's capabilities and limitations is required.

The goal of an educational intervention on autonomous vehicles is not to maximize trust of people, but to correctly calibrate trust for the current system. According to Ososky, et al (2013) suggest that improving mental models of system's capabilities and limitations will create more appropriate calibrations of trust. This improvement in calibration then gives users the freedom to interact with autonomy with appropriate reliance, minimizing negative performance outcomes.

Educating users with the intent of improving appropriate trust through accurate mental models is an important aspect of working with autonomous vehicles due to the implications of poor calibration. If users begin to rely to heavily on autonomy and it fails in a dire situation, it could lead to injury or worse. This could take form in secondary users who are driving near autonomous vehicles assuming that they should not worry about a given vehicle because of its autonomy capabilities. An educational intervention aims to improve the calibration between trust and autonomy capabilities to an appropriate level.

Research on autonomous vehicles is a budding area of research for those in the human factors field. Afterall these are not machines that people are working in conjunction with to complete a task, but machines that are responsible for user's and their families wellbeing. How people perceive AVs is paramount to the success of autonomous vehicles. Autonomous vehicles are a new technology that are still being developed and are not widely understood yet. Therefore, it is important that users properly understand the capabilities of these vehicles and that their trust is properly calibrated to those available capabilities. This relates directly to emotion and trust in an open mixed environment because of the possible negative effects that an elevated emotional state; or the implications of poorly calibrated trust explained above has on drivers. By using an educational intervention, like the one in this study, researchers hope to correctly calibrate user's trust with autonomy and then measure their positive and negative affect. It is hypothesized that the educational information about autonomous vehicles will induce negative emotions in participants, with trust correlating in a positive direction with affect. This hypothesis is based on the assumption that the public's view of autonomous vehicle's capabilities is greater than currently available and would trust AVs do more than they are capable of.

CHAPTER 4

METHODS

Design

This study uses a repeated measures design survey which was issued to 200 participants. This allowed for researchers to use a smaller sample size and collect data more efficiently using Amazon's MTurk tool and Qualtrics. This design allows researchers to analyze the differences that the intervention makes on each individual participant. Rather than relying on larger samples required for other research designs.

Participants

The current study's survey was delivered using Amazon's Mechanical Turk, and participants were selected based on age. Data were collected from 200 participants between the ages of 18-65. Of these 200 participants only 61 were used for analyses and of these 61 only six were under the age of 25; with the average age of the analysis sample being 33 years old. The oldest participant was 55 years old, despite the study being available to those up to 65, the next oldest participant was only 49 years. This age range allowed for a diverse group of participants that would have a driver's license that have adequate driving skills. Participants will not be excluded based on race or gender. Two hundred participants were recruited using Amazon's MTurk program and were only allowed to complete the survey if they had a 95% completion rate with over 500 completions; this helped to strengthen results because participants were known to be reliable.

Measures

Trust. This study will be employing the use of a trust scale derived from Jian et. al. (2000) to measure participants trust in autonomous vehicles before the study. Jian, Bisantz, and Drury (2000) approached the topic of trust with the intent to create a new scale for measuring trust. This scale has been validated by several other studies. The trust scale has 10 items that question participants on several aspects of their trust on a Likert scale. Researchers will then be able to compare these results with results from the Positive and Negative Affect Schedule to assess whether there is a correlation between trust and these emotional states. The scale used for the current study is in appendix A. The survey was scored using the framework laid out by previous research, where certain items were reverse coded, and others were not. Participant responses would then be summed up for an overall trust score, a high score indicates a high level of trust whereas a low score indicates the opposite. For example, item one on the trust scale states “Autonomous Vehicles are deceptive”. Participants would then rate their agreeance with the statement on a Likert scale between 1 and 7, 7 being extremely and 1 being not at all. This item would be reversed coded because marking a 7 would indicate a low trust response.

Emotions. To measure participants positive and negative affect researchers will be using the Positive and Negative Affect Schedule (PANAS) developed by Watson and Clark (1988). This 10-item scale allows for researchers to measure participant’s current positive and negative affect levels using a self-report survey method. PANAS uses a Likert scale which ranges from 1-5; 1 representing “very slightly or not at all” and 5 representing “extremely”. Participants are then presented with an adjective like “distressed” or “excited” and asked to rate how they feel during that given moment. The Positive and Negative Affect Schedule (PANAS) generates two scores, one by summing all the positive weighted questions (questions 1,3,5,9,10,12,14,16,17, &19 on the PANAS)and the other by summing the negatively weighted questions(questions 2,4,6,7,8,11,13,15,18,&20). Watson and Clark (1988) found that this scale is valid for different times in participants lives, ranging from momentary affect to affect within the last year. This allows for researchers to measures participant’s affect from a moment to moment basis or at a later date.

The PANAS has been used in a driving context by Hess et al. (2013) while measuring cognitive load and user experience while using a driving simulator. Researchers used interviews and the PANAS to identify positive driving experiences that resulted from critical situation while driving. Using those identified positive experiences the researchers created fake scenarios that were then delivered to participants using a low and high-fidelity driving simulator. Hess et al. then conducted further interviews with the PANAS to determine whether more positive experiences presented themselves during the simulation. The PANAS in this study was issued in the context of driving around autonomous vehicles.

Autonomous Vehicle Briefing. The briefing was used to ensure that all the participants had a baseline understanding of how automation works. Researchers wanted to examine the relationship between trust in AVs and knowledge of how autonomous vehicles perceive and navigate their environment. This information, which is included with the survey(See Appendix C) focused primarily on the actual systems that autonomous vehicles rely on to navigate the world (LiDAR, machine learning, etc). Researchers involved in designing this intervention decided on this baseline information about how AVs work because there was no way to determine the magnitude of priming from other information about autonomous vehicles (i.e. news stories or case studies). This briefing was also used to ensure that participants were taking the survey seriously, if participants were not able to score at least a 60% and improve on their pre test score their data was not included in the analyses. This pre and post knowledge test measured participants knowledge of the materials provided by researchers. The knowledge test (See Appendix C) consisted of 5 questions which were pulled directly from the briefing.

Procedure. Participants were required to consent to the survey before beginning the survey. The survey was delivered through Qualtrics and participants were given 45 minutes to complete the survey which includes a knowledge check about autonomous vehicles, the Jian (2000) trust scale, the Positive and Negative Affect Schedule, and a driving behavior survey. The driving behavior survey was a part of another student's thesis project and thus will not be analyzed for this study. Participants filled out these individual items twice, first as a pre-test before the delivery of educational material and second, as a post-test to measure the effect of the educational information. They then filled out a demographics survey which assessed whether they had a driver's license or not. Only data that showed the participants had read the material and could score a 60% or higher with an improvement in score on the post-test were used for data analysis; leaving 61 participants for analysis. This threshold was based on the fact that it is considered a passing grade for most academic levels.

CHAPTER 5

RESULTS

The results from the post PANAS and the post Jian Trust scale were analyzed using a Pearson correlation which compared positive affect, negative affect, and trust scores. There was a correlation between post positive affect and post trust [r=.513, n=61, p<.001]. This indicates that trust and positive affect have a moderate positive correlation. As trust increases so does positive affect, which creates a strong case to develop autonomous technology that is trustworthy. There was also a correlation between post negative affect and post trust [r=-.624, n=61, p<.001], indicating a negative correlation between negative affect and trust. These moderate correlations are summarized in scatterplot Figures 1 & 2, with the grey envelopes representing the confidence interval in the 95th percentile. The results indicate that trust moderately covaries with affect in the same direction. Therefore, researchers reject the null for the second hypothesis, trust acts as a covariate in the same direction as affect.

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Pre Positive Affect	61	10	50	33.66	8.742
Pre Negative Affect	61	10	45	17.80	10.020
Pre Jian Trust	61	22	84	61.25	16.231
Pre Knowledge Check	61	0%	40%	30.82%	12.948%
Post Knowledge Check	61	60%	60%	60.00%	0.000%
Post Positive Affect	61	10	50	33.84	9.365
Post Negative Affect	61	10	44	17.08	9.687
Post Jian Trust	61	12	84	62.51	15.698
Valid N (listwise)	61				

Table 1

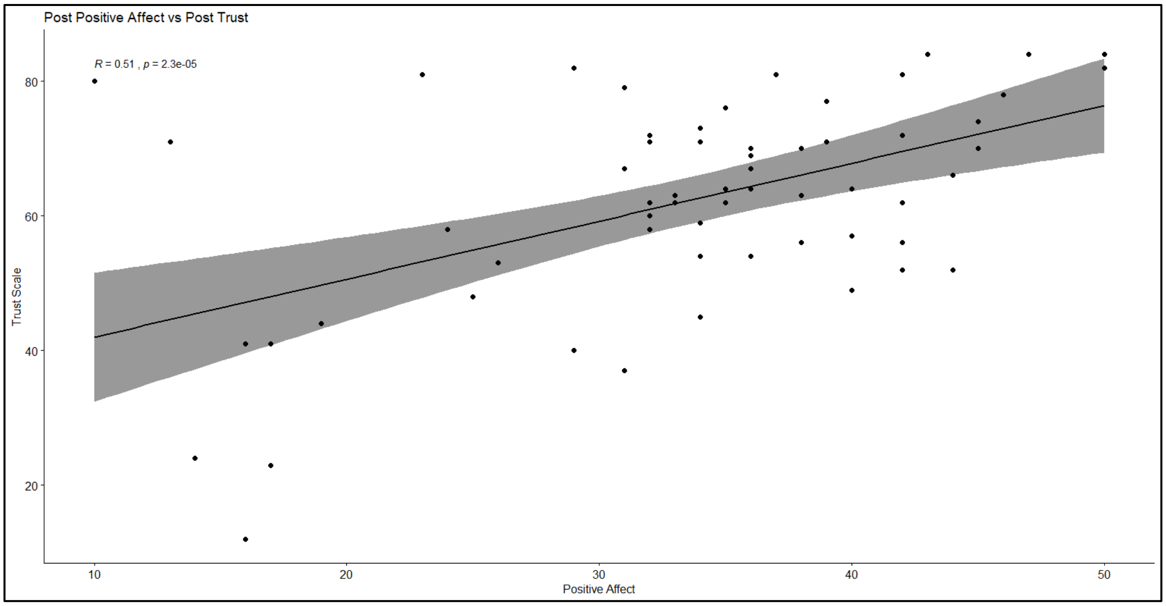

Figure 1: correlation of a post-test positive affect measure and post-test trust measure

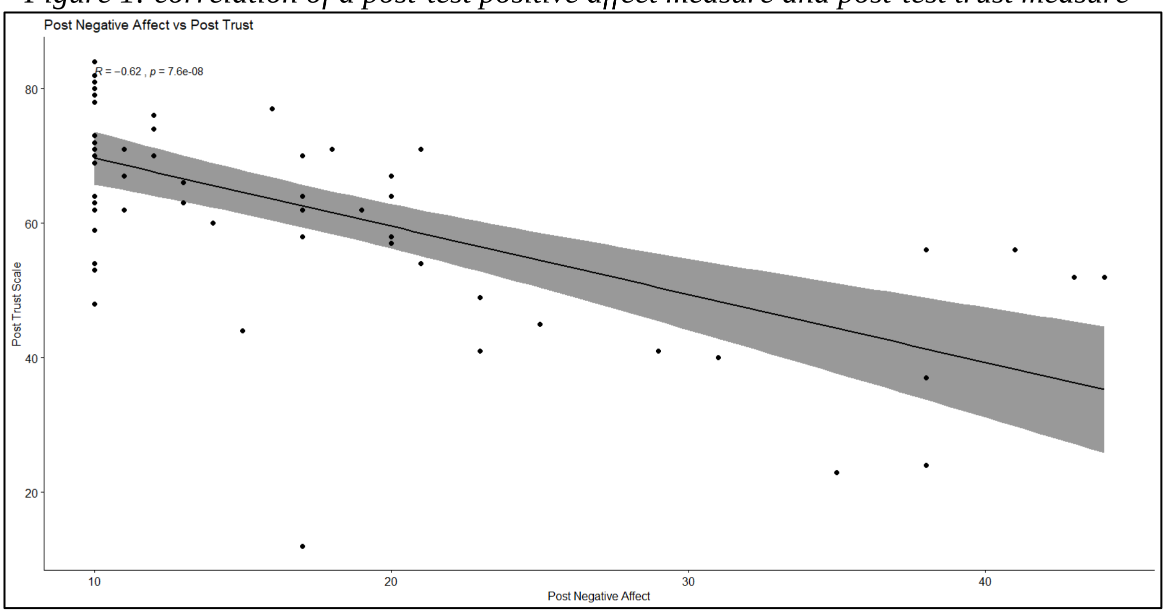

Figure 2: correlation of a post-test negative affect measure and post-test trust measure

To determine whether there was an effect from the educational intervention on participants affect scores two paired samples t-test were conducted to compare pre and post positive affect scores and pre and post negative affect scores. There was not a significant difference in scores for pre positive affect (M=33.66, SD=8.742) and post positive affect (M=33.84, SD= 9.365) conditions; *t*(60)=-.319, *p*=.751. For negative affect there was no significance found in scores for pre negative affect (M=17.8, SD=10.02) and post negative affect (M=17.08, SD=9.687); *t*(60)=1.081, *p*=.284. These results indicate that the educational intervention provided had no effect on participants affect. A t-test was also run on the participants pre (M=61.25, SD=16.231) and post (M=62.51, SD=15.698) trust scores and found no significance; *t*(60)=-1.647, *p*=.105. The descriptive statistics in *Table 1* show that participants have higher positive affect and trust towards AVs than they do negative affect and trust. Outliers existed in several of the analyses, however no single participant was consistently an outlier in all of the analyses so they could not be removed. Other analyses were done comparing the change of test score and trust score, and to compare age to trust. After conducting the Pearson correlation on score changes between the knowledge check test and the Jian trust scale, there was no significant correlation found, [r=-.014, n=61, p=.912]. This indicates that despite participants understanding of autonomous vehicles improving, it had no observable effect on their trust. For the correlational analysis between age and trust, there was a negative correlation found, [r=-.278, n=61, p=.030] indicating that as age goes up trust goes down.

CHAPTER 6

DISCUSSION

This survey set out to determine the effects of an educational intervention about autonomous vehicles on people's affect towards driving, and whether trust covaries with those emotions. The findings above indicate that the educational intervention had no effect on participants trust or affect towards driving, and the null hypothesis is accepted. However, there were moderate correlation found between emotions and trust, and age and trust. This research sought to examine the importance of designing automation with human driver's affect and trust in mind. However, this could be a result of inadequate power after the removal of poor data or the briefing being insufficient to affect the participants. The moderate effect between trust and affect is important to consider because of the implications for driving behavior. The literature indicates that emotions are important to consider while driving because of their impact on driving behavior. As shown in Cai, Lin, and Mourant (2007) drivers who are in excited or angry states tend to demonstrate poorer driving performance. Higher positive affect was shown to correlate with trust moderately in a positive direction. Regardless more research has to be done in order to draw more conclusions from this data. This exemplifies the importance of Lee and See's (2004) calibration, resolution, and specificity issue. Education about autonomous vehicles needs to be comprehensive and easily understood so that trust can be correctly calibrated to the AV, allowing for users to maximize autonomy and building better experiences.

For those purchasing AVs at their current level, an understanding of autonomous vehicles performance is important for those who will be interacting with them daily at these early stages. Owners of autonomous vehicles should have appropriately calibrated trust with the autonomy so that over reliance does not become a danger on the road. This should be on the companies selling these vehicles, because each company approaches autonomy differently it would not be realistic to expect the government or any other entity create these educational materials. Instead companies should be creating material based on their individual product and its capabilities for users.

Although the educational intervention in this study was not found to be significant, that may be due to limitations of this study explained later. Research can continue to support this issue by using advanced test beds designed to create real life situations without the risk. This could include simulator work or test beds like the one being developed at Arizona State University currently, CHARTopolis. CHARTopolis is a miniature city that includes traffic lights, stop signs, yielding turns, and other modular traffic environments that allows researchers to investigate autonomous vehicles in conjunction with human behavior. This type of testbed, which the author helped develop, minimizes risk but still allows for mistakes to happen while interacting with autonomy.

Limitations

Limitations from the current study involve the weakness of performing an online survey, which does not allow probing certain answers or responses. Without being there to proctor surveys there is no guarantee that participants took their time to answer questions honestly and with accuracy. Proctors would be able to observe participants if they were rushing and note the issue. This research relies on participants taking their time to complete the study and placing themselves in different driving situations, which is why the 60% post briefing grade was chosen. This number helped eliminate any participants rushing through the survey just to receive compensation. This risk was also mitigated by using Qualtrics’s tool that requires participants to remain on certain pages for a set amount of time, in this case it was the educational briefing in which participants were required to stay on the page for at least three minutes. For future replications of this survey, in-person moderated sessions should be used instead of the remote unmoderated style used for the survey in this study. This would allow for researchers to ensure their participants take their time to fill out the survey. The online survey delivery method, MTurk, essentially uses a participant pool that is trying to maximize the amount of money they can make quickly which amplifies the issue of participants rushing through the survey. Using an in-person survey would also allow for participants to clarify any questions or misunderstandings they had, creating a more thorough understanding of the reading. For an in-person survey, a power analysis would need to be conducted to avoid wasting excessive resources. This survey did not use one due to the assumption that the initial 200 participants would be adequate, however the loss of over 100 participants could not be predicted. Another limitation for this survey could be the researcher designed intervention itself, which was designed to be quick to read and easy to understand for time restrictions. It is also recommended to use a video to explain the information about autonomous vehicles in any replications of this survey. Findings presented by Mayer (2012) indicate that multimedia learning is more effective for information transfer in learning environments. The video should contain more information about the limitations and benefits of the technology that makes up autonomous vehicles. The briefing in this study was not able to delve into these limitations and benefits enough. This likely led to there being very little change between the pre-test and post-test scores. The final issue with the online survey is that since it is anonymous, researchers have no way of confirming whether participants have driver's licenses without taking the ID number and confirming with motor vehicle divisions. Doing this would be directly violate the participants anonymity, so researchers must trust that participants filled out the demographics truthfully. To combat this limitation researchers would recommend running an in-person study so that moderators could check licenses in person, this would validate their driving experience and would not require researchers to record personal information. Researchers would also recommend developing a more powerful briefing that may affect the participants more. One final weakness that can be pointed out with survey is that they only measure how a participant thinks that they would react in a specific scenario and their real responses in that given scenario could very well be much different. This is a very important consideration while considering future research projects, one that can be partially overcome by using simulators and testbeds like those of CHARTopolis. Without being able to debrief participants it is difficult to identify the possible reasons for outliers in this study, like those seen in figure 1. However, they likely have to do with the online distribution of the survey, and the inability of the participants to be monitored by moderators. It is also possible that outliers did not understand the instructions of the survey.

CHAPTER 7

CONCLUSION

This study will contribute to the field of human automation interaction as it delves into the emotional aspects that can be brought on by autonomy. Despite not finding any significant results in the pre and post-test t-tests there is space for improvement on this survey that could tease out the effects that this survey missed. The lack of significance in the t-tests presumably has to do with the limitations discussed above. However, it could also be a result of an over saturation of autonomous vehicles in media that participants already had set opinions that were not swayed by the educational intervention. Educational interventions could still be useful in this field of research, but it is recommended to improve on this study's designs if one were to be implemented. The moderate correlation between trust and affect trust and age, are important findings to consider regardless of the t-test results. At the very least, the existence of the found correlation and lack of significance from the t-tests indicates that emotion and trust are related outside of this study.

Up to this point there has not been a lot of studies that consider how autonomous technology affects human emotions and whether there are concerns about this interaction. Based on some of the literature above, this research needs to be continued as technology becomes more and more advanced and independent. This study is largely exploratory and indicates future research that will need to be addressed using test beds like Arizona State University's CHARTopolis. Continued research in this area could be done by creating different autonomy that is more or less trustworthy to see how participants react. This could be done using simulators or by the CHARTopolis test bed. By using autonomous robots in place of vehicles that differ in sophistication by designing them to have various levels of consideration for other drivers.

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APPENDIX A

TRUST SCALE FOR AUTONOMOUS VEHICLES

Derived from Jian et al, (2000)

***Please rate how much you agree with the following statements**

Note that; 1=Not at all, 7=extremely.

1. **Autonomous vehicles are deceptive**

   1 2 3 4 5 6 7

2. **I am confident in autonomous vehicles ability to perform**

   1 2 3 4 5 6 7

3. **Autonomous vehicles will have a harmful or injurious out come**

   1 2 3 4 5 6 7

4. **I am suspicious of autonomous vehicles intent, action, or outputs**

   1 2 3 4 5 6 7

5. **Autonomous vehicles behave in underhanded manners**

   1 2 3 4 5 6 7

6. **I am wary of autonomous vehicles**

   1 2 3 4 5 6 7

7. **Autonomous vehicles have integrity**

   1 2 3 4 5 6 7

8. **I can trust autonomous vehicles**

   1 2 3 4 5 6 7

9. **I am familiar with autonomous vehicles**

   1 2 3 4 5 6 7

10. **Autonomous vehicles are reliable**

    1 2 3 4 5 6 7

APPENDIX B

POSITIVE AND NEGATIVE AFFECT SCEHDULE (PANAS)

Positive and Negative Affect Schedule (PANAS)

This scale consists of a number of words that describe different feelings and emotions. With regards to driving around autonomous vehicles, read each item and then mark the appropriate answer in the space next to that word. Indicate to what extent you are feeling this way right now towards the idea of driving in close vicinity autonomous vehicles. Use the following scale to record your answers.

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

#	Score	I Feel ...
1		Interested
2		Distressed
3		Excited
4		Upset
5		Strong
6		Guilty
7		Scared
8		Hostile
9		Enthusiastic
10		Proud
#	**Score**	**I Feel ...**
11		Irritable
12		Alert
13		Ashamed
14		Inspired
15		Nervous
16		Determined
17		Attentive
18		Jittery
19		Active
20		Afraid

APPENDIX C
CHART SURVEY

CHART Survey - 2019

Start of Block: Default Question Block

Q1 We are graduate students working under Professor Nancy Cooke in the Ira A. Fulton Schools of Engineering at Arizona State University. We are conducting a research to examine factors affecting emotion, trust and driving behavior around autonomous cars. We are inviting your participation, which will involve a survey followed by some demographic questions. You have the right to not answer and questions, and may stop participating at any time. Your participation in this study is voluntary. If you choose not to participate or to withdraw from the study, there will be no penalty. If you do not complete the study, you may not receive any/full compensation. Your responses will be used to contribute to the completion and potential publication of graduate thesis projects. The benefits to you include compensation via Amazon M-Turk and contribution to the scientific community. There are no foreseeable risks or discomforts to your participation. You will be given 45minutes to complete this survey. You will be compensated $1 through the Amazon M-Turk portal for your participation in this study. Confidentiality will be maintained throughout the duration of the research study and will not be violated at any point while the data is kept. Only individuals directly associated with this project will have secure access to the data. We will not ask your name or any other identifying information in this survey. For research purposes, an anonymous numeric code will be assigned to your responses. However, your Amazon M-Turk worker ID number will be temporarily stored in order to pay you for your time; this data will be deleted as soon as it is reasonably possible. You have the of option of making your personal information private by changing your M-Turk settings through Amazon. The results of this study may be used in reports, presentations, or publications but your name will not be used, and only group characteristics reported. If you have any questions concerning the research study, please contact the research team at: Dr. Nancy Cooke at Nancy.cooke@asu.edu, Sterling Martin at smarti57@asu.edu, or Taylor Reagan at treagan1@asu.edu. If you have any questions about your rights as a participant in this research, or if you feel you have been placed at risk, you can contact the Chair of the Human Subjects Institutional Review Board, through the ASU Office of Research Integrity and Assurance, at (480)965-6788   You must be 18 years or older to participate in this study. By selecting “I agree” below you are agreeing to be part of the study and that you are 18 years of age or older. Please note: You may not return to questions once your answer has been submitted. THIS SURVEY CAN ONLY BE COMPLETED ONCE. IF YOU HAVE ALREADY COMPLETED IT ONCE, YOU WILL NOT BE PAID.

☐ I agree to participate in this study, and confirm that I am at least 18 years of age

End of Block: Default Question Block

Start of Block: Pre PANAS

Q2 This scale consists of a number of words that describe different feelings and emotions. With regards to driving around autonomous vehicles, read each item and then mark the appropriate answer in the space next to that word. Indicate to what extent you are feeling this way right now towards the idea of driving in close vicinity autonomous vehicles. Use the following scale to record your answers.

	1- Strongly Disagree	2- Disagree	3-Neutral	4-Agree	5-Strongly Agree
Interested	o	o	o	o	o
Distressed	o	o	o	o	o
Excited	o	o	o	o	o
Upset	o	o	o	o	o
Strong	o	o	o	o	o
Guilty	o	o	o	o	o
Scared	o	o	o	o	o
Hostile	o	o	o	o	o
Enthusiastic	o	o	o	o	o

Proud	○	○	○	○	○
Irritable	○	○	○	○	○
Alert	○	○	○	○	○
Ashamed	○	○	○	○	○
Inspired	○	○	○	○	○
Nervous	○	○	○	○	○
Determined	○	○	○	○	○
Attentive	○	○	○	○	○
Jittery	○	○	○	○	○
Active	○	○	○	○	○
Afraid	○	○	○	○	○

End of Block: Pre PANAS

Start of Block: Pre Jian

Q3 Please rate how much you agree with the following statements

	1= Not at All	2	3	4	5	6	7= Extremely
Autonomous vehicles are deceptive	○	○	○	○	○	○	○
I am confident in an autonomous vehicle's ability to perform	○	○	○	○	○	○	○
Autonomous Vehicles will have a harmful or injurious outcome	○	○	○	○	○	○	○
I am suspicious of autonomous vehicles intent, action, or ouputs	○	○	○	○	○	○	○
Autonomous vehicles behave in underhanded manners	○	○	○	○	○	○	○
I am wary of autonomous vehicles	○	○	○	○	○	○	○
Autonomous vehicles have integrity	○	○	○	○	○	○	○
I can trust autonomous vehicles	○	○	○	○	○	○	○
I am familiar with autonomous vehicles	○	○	○	○	○	○	○
Autonomous vehicles are reliable	○	○	○	○	○	○	○
The autonomous vehicles provide security	○	○	○	○	○	○	○

The autonomous vehicle is dependable	○	○	○	○	○	○	○

End of Block: Pre Jian

Start of Block: Pre driving behaviour

Q4 Below is a list of behaviors that may or may not be relevant to your actions [or hypothetical actions] concerning autonomous vehicles. Please indicate how frequently you perform, or would perform, each of these items when driving in close vicinity to autonomous vehicles. Please indicate what you generally do, or would do, not what you think you should do.

	1-Not at all	2	3	4	5	6	7-Strongly
I slow down when approaching intersections, even when the light is green.							
I maintain a large distance between myself and the driver (Autonomous vehicle) in front of me							
I try to put distance between myself and other cars (Autonomous vehicles).							
I maintain my speed in order to calm myself down.							
I try to stay away from other cars (Autonomous vehicles).							
I decrease my speed until I feel comfortable.							

During bad weather, I drive more cautiously than other [autonomous] vehicles on the road.	○	○	○	○	○	○	○

End of Block: Pre driving behaviour

Start of Block: Autonomous Vehicle Knowledge Check

Q14 Besides LIDAR, what other technologies do autonomous vehicles use to perceive their environment?

○ Radar, WiFi, and Bluetooth

○ Traffic cameras, and other vehicles LIDAR

○ Cameras, GPS, and Radar

Q23 What are the drawbacks of LIDAR?

○ Only works well in short range scenarios, and LIDAR systems can interfere with one another when in close proximity

○ It does not work well in short range scenarios

○ It does not work well in mid range distances, and can only detect other LIDAR systems

Q15
What method do engineers use to "teach" autonomous vehicle how to operate in the real world?

- ◯ Hard coding
- ◯ Robot Awareness
- ◯ Machine Learning

Q19

What is the optimal design for combining programming and sensors in autonomous vehicles?

- ◯ There is currently no consensus
- ◯ LIDAR, radar, Robot Awareness
- ◯ Machine Learning, traffic cameras, radar

Q26 At what level of automation can a vehicle drive itself under all conditions?

- ◯ Level 5
- ◯ Level 3
- ◯ Level 2

End of Block: Autonomous Vehicle Knowledge Check

Start of Block: Briefing info on autonomous vehicles

Q9 There is a 3 minute timer on this page, so please take your time to read through the information below. There will be a second quiz to test your understanding of autonomous vehicles. To fully understand where autonomous vehicles currently are in development one needs to understand the different levels of automation. There are currently six different levels of autonomy that range from 0- No Automation at all and 5- full automation. Below is a graphic developed by the Society of Automotive Engineers to explain the different levels.*Society of Automotive Engineers Automation Levels [2]*. Autonomous Vehicles (AVs) combine multiple different kinds of state-of-the-art technology to navigate the world without incident. This whole process begins when companies drive standard vehicles around a city with LIDAR attached to build a 3D map which can then be used by AVs later to compare and understand where they currently are [5][6]. LIDAR is a detection system that uses the same principles of radar, but instead of using radio waves it uses lasers to detect nearby objects. This system does have some flaws however, LIDAR is limited to short range use only, and can often be affected by severe weather. LIDAR systems are also known to interfere with each other if multiple systems are in close proximity to one another [5]. The limitations of LIDAR create a need for redundancy, meaning multiple sensors must overlap to ensure system accuracy. Cameras, GPS, and radar are used to add layers to AV's perception system, creating a wealth of raw data for processing. This additional technology is meant to aid AV's in perceiving and classifying potential obstacles such as cyclists, street lights, and pedestrians [5][1][3].Ultrasonic sensors in the wheels are also used to detect curbs and other parked vehicles while parking [1]. In order to process the massive amount of raw data being collected, engineers had to develop software that enables AV's to process the data, and use that information to inform actions in real time. Engineers started by programming strict base rules into AV's, such as stopping at a red light and going at a green light [5][3]. However, since engineers cannot predict every scenario, companies use machine learning to "teach the car" by analyzing massive amounts of data [5] These cars are observing and learning from human drivers on what to do in a variety of different situations, such as what to do when a large rock rolls into the street [4]. Machine learning is a complicated process; "because neural networks (computer systems modeled on the human brain and nervous system) learn from such large amounts of data, relying on hours or even days of calculations, they operate in ways that their human designers cannot necessarily anticipate or understand. There is no means of determining exactly why a machine reaches a particular decision" [4]. A specific aspect of machine learning can be found in Alphabet's, Google's parent company, autonomous car company, Waymo. Rather than code what a pedestrian looks like, Waymo created an algorithm so the computer could learn what they looked like on its own[4]. Essentially the algorithm to learn is developed and then images of a pedestrian next to a road are fed into the algorithm until the system is capable of identifying pedestrians. AV's use a combination of the strict rules they are programmed with and their machine learning capabilities to interpret perceptual data, which they then use to plot a course, and then send the necessary signals to execute that course to the actuator systems (accelerator, steering wheel, breaks etc) of the AV. [6][3] Currently, despite the multitude of companies developing AV's, there is no consensus on the correct framework of AVs and how programming and sensors should be combined for an optimal design[3].

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End of Block: Briefing info on autonomous vehicles

Start of Block: AV Knowledge Check 2

X→

Q27 Besides LIDAR, what other technologies do autonomous vehicles use to perceive their environment?

- ○ Radar, WiFi, and Bluetooth
- ○ Traffic cameras, and other vehicles LIDAR
- ○ Cameras, GPS, and Radar

Q28 What are the drawbacks of LIDAR?

- ○ Only works well in short range scenarios, and LIDAR systems can interfere with one another when in close proximity
- ○ It does not work well in short range scenarios
- ○ It does not work well in mid range distances, and can only detect other LIDAR systems

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Q29
What method do engineers use to "teach" autonomous vehicle how to operate in the real world?

- ○ Hard coding
- ○ Robot Awareness
- ○ Machine Learning

Q30

What is the optimal design for combining programming and sensors in autonomous vehicles?

- ○ There is currently no consensus
- ○ LIDAR, radar, Robot Awareness
- ○ Machine Learning, traffic cameras, radar

Q31 At what level of automation can a vehicle drive itself under all conditions?

- ○ Level 5
- ○ Level 3
- ○ Level 2

End of Block: AV Knowledge Check 2

Start of Block: Post PANAS

Q5 This scale consists of a number of words that describe different feelings and emotions. With regards to driving around autonomous vehicles, read each item and then mark the appropriate answer in the space next to that word. Indicate to what extent you're feeling this way right now towards the idea of driving in close vicinity autonomous vehicles. Use the following scale to record your answers.

	1- Strongly Disagree	2- Disagree	3-Neutral	4-Agree	5-Strongly Agree
Interested	◯	◯	◯	◯	◯
Distressed	◯	◯	◯	◯	◯
Excited	◯	◯	◯	◯	◯
Upset	◯	◯	◯	◯	◯
Strong	◯	◯	◯	◯	◯
Guilty	◯	◯	◯	◯	◯
Scared	◯	◯	◯	◯	◯
Hostile	◯	◯	◯	◯	◯
Enthusiastic	◯	◯	◯	◯	◯
Proud	◯	◯	◯	◯	◯
Irritable	◯	◯	◯	◯	◯
Alert	◯	◯	◯	◯	◯
Ashamed	◯	◯	◯	◯	◯

Inspired	○	○	○	○	○
Nervous	○	○	○	○	○
Determined	○	○	○	○	○
Attentive	○	○	○	○	○
Jittery	○	○	○	○	○
Active	○	○	○	○	○
Afraid	○	○	○	○	○

End of Block: Post PANAS

Start of Block: Post Jian

Q6 Please rate how much you agree with the following statements

	1= Not at All	2	3	4	5	6	7= Extremely
Autonomous vehicles are deceptive	○	○	○	○	○	○	○
I am confident in an autonomous vehicle's ability to perform	○	○	○	○	○	○	○
Autonomous Vehicles will have a harmful or injurious outcome	○	○	○	○	○	○	○
I am suspicious of autonomous vehicles intent, action, or ouputs	○	○	○	○	○	○	○
Autonomous vehicles behave in underhanded manners	○	○	○	○	○	○	○
I am wary of autonomous vehicles	○	○	○	○	○	○	○
Autonomous vehicles have integrity	○	○	○	○	○	○	○
I can trust autonomous vehicles	○	○	○	○	○	○	○
I am familiar with autonomous vehicles	○	○	○	○	○	○	○

Autonomous vehicles are reliable	○	○	○	○	○	○	○
The autonomous vehicles provide security	○	○	○	○	○	○	○
The autonomous vehicle is dependable	○	○	○	○	○	○	○

End of Block: Post Jian

Start of Block: Post Driving Behavior

Q7 Below is a list of behaviors that may or may not be relevant to your actions [or hypothetical actions] concerning autonomous vehicles. Please indicate how frequently you perform, or would perform, each of these items when driving in close vicinity to autonomous vehicles. Please indicate what you generally do, or would do, not what you think you should do.

	1-Not at all	2	3	4	5	6	7-Strongly	
I slow down when approaching intersections, even when the light is green.	○	○	○	○	○	○	○	○
I maintain a large distance between myself and the driver (Autonomous vehicle) in front of me	○	○	○	○	○	○	○	○
I try to put distance between myself and other cars (Autonomous vehicles).	○	○	○	○	○	○	○	○
I maintain my speed in order to calm myself down.	○	○	○	○	○	○	○	○
I try to stay away from other cars (Autonomous vehicles).	○	○	○	○	○	○	○	○
I decrease my speed until I feel comfortable.	○	○	○	○	○	○	○	○

During bad weather, I drive more cautiously than other [autonomous] vehicles on the road.	○	○	○	○	○	○	○	○

End of Block: Post Driving Behavior

Start of Block: Demographics

Q41 Have you ever driven in close proximity of an autonomous vehicle?

○ Yes

○ No

○ Unsure

Q45 Do you have a current driver's license? If so, how many years have you had your license?

○ No

○ Yes, 10 or fewer

○ Yes, 11-30

○ Yes, 31 or more

Q36 How old are you?

____

Q38 What is your sex?

- ○ Male
- ○ Female
- ○ Other

Q40 Highest education level you have received:

- ○ Elementary School
- ○ High School
- ○ College- Undergraduate
- ○ College- Graduate

End of Block: Demographics

Start of Block: Block 11

Q25 Thank you for taking our survey! The MTURK code is posted below!

448629246

End of Block: Block 11