The Effects of an Educational Intervention on Driving Behavior and Trust

by

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ABSTRACT

Vehicular automation and autonomy are emerging fields that are growing at an exponential rate, expected to alter the very foundations of our transportation system within the next 10-25 years. A crucial interaction has been born out this new technology: Human and automated drivers operating within the same environment. Despite the well-known dangers of automobiles and driving, autonomous vehicles and their consequences on driving environments are not well understood by the population who will soon be interacting with them every day. Will an improvement in the understanding of autonomous vehicles have an effect on how humans behave when driving around them? And furthermore, will this improvement in the understanding of autonomous vehicles lead to higher levels of trust in them? This study addressed these questions by conducting a survey to measure participant's driving behavior and trust when in the presence of autonomous vehicles. Participants were given several pre-tests to measure existing knowledge and trust of autonomous vehicles, as well as to see their driving behavior when in close proximity to autonomous vehicles. Then participants were presented with an educational intervention, detailing how autonomous vehicles work, including their decision processes. After examining the intervention, participants were asked to repeat post-tests identical to the ones administered before the intervention. Though a significant difference in self-reported driving behavior was measure between the pre-test and post-test, there was no significant relation found between improvement in scores on the education intervention knowledge check and driving behavior. There was also no significant relation found between improvement in scores on the education intervention knowledge check and the change in trust scores. These findings can be used to inform

autonomous vehicle and infrastructure design as well as future studies of the effects of autonomous vehicles on human drivers in experimental settings.

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CHAPTER1

INTRODUCTION

Autonomous technologies are ever-growing and expanding into new fields and have recently been applied in increasingly high stakes sectors of development, including aviation, surgery, and automobiles. These increasingly risky applications have fueled questions and concerns regarding the effects autonomy has on the individuals who are interacting with it. The automotive industry has begun mass production of automated vehicles, a move that likely constitutes the most significant change to transportation in living memory. The introduction of this new technology may negatively affect drivers who are untrustworthy of automation. This area has already proven to be extremely dangerous without the advent of automation, with traffic accidents causing over 37,000 deaths and over 2.3 million injuries per year in the United States (Road Crash Statistics). In 2016 alone, almost 1,000 fatalities and over 100,000 injuries were caused by traffic accidents in the state of Arizona, one of the first states in the nation to introduce autonomous vehicles, from companies such as Uber and Waymo, into the state's transportation system (Arizona Department of Transportation, 2016). Automation is an extremely high-level resource, and introducing it to driving, one of our most volatile environments, is likely to cause significant changes to our behaviors.

The introduction of automated driving to our roadways will likely lead to a driving environment that includes vehicles with varying degrees of automation. Considering our unfamiliarity with these situations, and their potentially deadly implications, it is necessary to take steps to understand the implications such technology will have on our driving experiences.

In order to begin assessing the different ways the introduction of automated vehicles could potentially affect transportation environments, it is necessary to identify the effects these technologies are having on driving behaviors, and whether these effects make roadways more hazardous. Once these effects have been established, researchers can begin to understand how they can be accounted for, and mitigated, if necessary.

The current study uses an exploratory survey to examine the effects of an educational intervention regarding autonomous vehicles on participant's self-reported driving behaviors, and how these driving behaviors correlate with trust of autonomous vehicles. The goal of this research is to determine if knowledge of information about autonomous vehicles has an effect on self-reported driving behaviors, and therefore inform future studies, as well as autonomous vehicle design and implementation. This thesis will determine if presenting participants with factual information about autonomous vehicles, and how they function, via an educational intervention will affect their self-reported driving behaviors. Schaefer (2017) has shown that, in order to successfully collaborate with intelligent agents, humans must be able to understand the agent's decision-making process, which is currently not the case in regard to automated vehicles. Following this line of reasoning, it is hypothesized that the educational intervention about autonomous vehicles will lead to a significant change in reported driving behavior from the pre-test to post-test. It is also hypothesized that a better understanding of how autonomous vehicles work will lead to an increase in trust, so that trust scores will positively correlate with scores on the knowledge check of the educational intervention.

CHAPTER 2

BACKGROUND

Perceptions of Autonomy and Autonomous Vehicles

A variety of existing perceptions regarding autonomous vehicles are present in human drivers, and these differing perceptions are likely to affect how each individual responds to autonomous vehicles. The population of drivers upset by autonomous vehicles, because of reasons ranging from anxiety about the technology to individuals who feel that the autonomous vehicles may simply impede their way, is especially concerning. A survey conducted by TRL Limited (Hyde, Dalton, & Stevens, 2017) found that, despite 81% of respondents agreeing or strongly agreeing with the sentiment that “driverless cars are a good idea”, only 55% of respondents agreed or strongly agreed with the statement, “I can trust a driverless vehicle”. In the freeform response section of the survey, the most frequently raised concerns had to do with software security, and the interaction of non-autonomous vehicle and autonomous vehicles on the roadways. Another survey (Schoettle & Sivak, 2014), examining public opinion about autonomous and self-driving vehicles, showed that 87.3% of respondents expressed some level of concern over the use of self-driving vehicles. These findings suggest that, though the general public may feel that autonomous vehicles are a good concept, their introduction to public roadways may be faced with significant concerns and trust issues.

In another study (Liang & Lee, 2017), researchers found that 20.1% of participants reported being slightly afraid to afraid of autonomous robots and artificial intelligence, and 18.5% reported being afraid to very afraid. These results are particularly alarming when considering researchers also discovered that participants did not discern among their fear of robots or fear of artificial intelligence, with findings suggesting that such a distinction may not be relevant to the general population. This general lack of discernment amongst the population suggests that the significant levels of fear reported by 38.6% of participants may extend towards autonomous vehicles as well.

In 2018, Hulse, Xie, and Galea conducted a survey that examined the perceived risk of being: the driver of a car, rider of a motorcycle, rider of a bicycle, passenger of a human operated train, passenger of an autonomous train, passenger of a human operated car, passenger of an autonomous car, pedestrian around a human operated car, and pedestrian around an autonomous car. The results of the survey show that, in general, people perceived being a passenger of an autonomous car as riskier than being the passenger of human operated car, however, being a pedestrian around an autonomous car was perceived as less risky than being a pedestrian around a human operated car. Perceptions of risk associated with autonomous vehicles vary widely by individual and situation, and this variation is important to consider when examining the perspective of human drivers operating in the same environment as autonomous vehicles, which is a notable gap in the research. It is possible that human drivers may perceive autonomous vehicles to be riskier than other human drivers, which could in turn affect their driving behaviors in that situation and potentially create a more dangerous driving environment.

The above literature establishes that there is a significant portion of the population who may negatively perceive autonomous vehicles. Much of this population will likely be interacting with autonomous vehicles on roadways in the near future, the effects of which are largely unknown to researchers. The unknown effects of these negative perceptions could lead to significantly more hazardous driving environments; a concern that must be considered as autonomous vehicles become even more prevalent in the 21st century.

Driving Behaviors

It is plausible that negative perceptions and feelings towards autonomous vehicles could have a significant impact on driving behavior. In fact, research has shown that negative emotions or moods can interact with risk perception to affect driving risk attitudes (Hu, Xie, & Li., 2013). Results showed that drivers with negative emotions showed a higher perception of traffic risk compared with drivers with positive or neutral emotions. These drivers with negative emotions were also shown to have a higher receptivity of risky driving, and higher self-reported risky driving behaviors. If drivers were to associate autonomous vehicles with negative emotions or feelings, it could lead to an increase in risky driving behavior and altered driving risk attitudes around autonomous vehicles, potentially facilitating an increase in the frequency of traffic accidents.

A report conducted by the NHTSA has shown that when a driver feels threatened by another driver, their driving behavior often changes as a result (Royal, 2003). It was reported that 43% of drivers responded to feeling threatened by stopping or slowing down, 20% moved their vehicle away from the perceived threat, 12% responded with an aggressive action towards the other driver, and 17% had no response to the perceived threat. These results not only show that the majority of drivers, 83%, modify their driving behavior in response to a threat, but that those modifications are varied and unpredictable. Research by Rhodes and Pivik (2011) has shown that risk perception is a significant factor in behavioral decision making for drivers. It is possible that significant changes to the driving environment, such as autonomous vehicles, may be perceived as risky by human drivers. In order to ascertain the potential issues human drivers may face within a driving environment in which autonomous vehicles are present, it is necessary to consider that autonomous vehicles may be viewed as a critical change to a driver's environment, and possibly as a threat, and therefore may significantly affect driving behaviors. Because of the known presence of negative perceptions towards autonomous vehicles and the possibility that some drivers may view autonomous vehicles as risky or a threat, it is critical to consider the presence of research that shows these views and perceptions have significant effects on driving behavior.

System Transparency and Trust

For any human-autonomy interaction to successfully achieve a shared goal, both the human and the intelligent agent must be able to satisfactorily anticipate the actions of each other (Klein, Woods, Bradshaw, Hoffman & Feltovich, 2004). The principle issue concerning interaction between human drivers and autonomous vehicles is that some human drivers do not believe they can anticipate the actions of autonomous drivers at a satisfactorily safe rate. Without the assurance of predictability, it will be nearly impossible for human drivers to maintain the same driving behaviors around autonomous vehicles, as they do around other humans.

According to Schaefer (2017), understanding an intelligent agent's decision-making process and objectives are critical components to successful collaboration. Autonomous vehicles lack effective means to communicate their decision-making process and objectives to human drivers. There is also a level of action prediction involved with minute movements of human drivers (e.g. slight drift towards a lane before turning on the blinker and changing lanes) that autonomy will effectively eliminate. Without the shared mental model for decision making processes, human drivers will be more likely to make risk-avoidant maneuvers in the presence of autonomous vehicles.

This shared understanding of decision-making processes and objectives are integral components of trust in autonomous vehicles. In 2015, Choi and Ji performed a study to investigate what factors drive people to trust autonomous vehicles and proposed three dimensions for trust in an autonomous vehicle: system transparency, technical competence, and situation management. They define system transparency as the degree to which users can predict and understand the operating of autonomous vehicles. Technical competence is defined as the degree of user perception on the performance of the autonomous vehicles. Situation management refers to the user's belief that he or she can recover control in a situation whenever desired. Each of these three factors were found to have significant effects ($p < .001$) on trust. The study used thirty questions to measure ten separate constructs: behavioral intention, perceived usefulness, perceived ease of use, perceived risk, external locus of control, sensation seeking, and trust, which also had three second-level constructs that included system transparency, technical competence, and situation management. System transparency, technical competence, and situation management accounted for 47.4% of variance in the case of the trust construct.

As discussed in Lyons' (2013) article considering an Intentional model for human-robot interaction, robots and autonomous systems are designed for particular purposes, and their physical appearance affords cues to the user about their functionalities. In the case of vehicular automated systems, Lyons (2013) specifically mentions the lack of opportunity for a direct linkage between function and physical appearance. Autonomous vehicles currently lack the means to fully communicate their intended actions to both passengers as well as other drivers; though the “why” aspect (purpose of the autonomous vehicle) is arguably quite clear, the “how” aspect (decision making processes) of its operation remains ambiguous. making it difficult for the system’s users to understand the intent of the system. This lack of opportunity for autonomous vehicles to communicate the system’s intentions leads to a specific lack of system transparency, increasing the vulnerability of trust in that dimension. In a 2015 study, Koo, Ju, Steinart, Leifer, and Nass discovered that, in semi-autonomous driving, explanations of the vehicle’s imminent autonomous actions affected driving performance. Messages that provided only information describing actions (e.g., “The car is braking”) resulted in poor driving performance, whereas drivers preferred information describing the reasoning behind actions (e.g., “Obstacle ahead”) which led to a better driving performance. However, when both information describing actions and the reasoning behind them was provided, it resulted in the safest driving experience. These results support the findings of Klein et. al. (2004), Schaefer (2017), and Lyons (2013) as well as supporting the idea that system transparency is a particularly vulnerable aspect of trust in autonomous vehicles.

Considering that the aspect of system transparency is especially important in trust of autonomous vehicles, that increased trust has a negative effect on risk perception (Choi and Ji, 2015), and that risk perception is positively correlated with risky driving behavior (Hu, Xie, & Li, 2013) it is reasonable to believe that increasing system transparency could lead to a significant change in driving behavior. Because trust of autonomous vehicles is linked with risk perception and driving behavior, appropriate calibration of trust is crucial to ensuring the safety of drivers in mixed autonomy driving environments.

Calibration of Trust

In order for any autonomous agent and human interaction to be safe and successful, the human must be able to trust the agent. However, research suggests that it is possible for humans to be too trusting of the automated technologies that they interact with, leaving themselves vulnerable to harm. Andersen, Köslich, Pedersen, Weigelin, and Jensen (2017) conducted an experiment in which participants, inside a simulator, had either no information, correct information, or false information about the state of traffic in the immediate environment, and were told they could assume control of the vehicle at any time. Results showed that a lack of transparency in an autonomous vehicle's actions can lead to situations in which the driver does not understand what the car is doing or why it is doing it. This also led to drivers' inability to detect the errors of the autonomous vehicle, regardless of how apparent they were. This lack of action transparency could extend to other human drivers that interact with the autonomous vehicle, dramatically increasing the associated risk of those interactions.

Ososky, Schuster, Phillips, and Jentsch (2013) described, using the mental model theory, how the understanding of the system, including how it operates, its capabilities, and its limitations, contributes to trust in human-robot teams. Specifically, the research suggests that shared mental models, including the understanding of the task and its relevant equipment, and of team members and their interaction, lead to more appropriate calibrations of trust. The appropriate calibration of trust ensures that humans do not over-rely or under-rely on their robotic (or autonomous) teammate, resulting in better team performance. The idea of improving calibration of trust through shared mental models can be applied to mixed autonomy driving environments, with the goal being to educate human drivers on the autonomous vehicles they are interacting with, and how they operate. An educational intervention regarding autonomous vehicles, and how they operate, aims to improve the calibration of trust in those autonomous vehicles, thereby creating an accurate shared mental model.

The imminent introduction of autonomous vehicles to human driver occupied roadways poses both great benefit and great risk. Individuals' opinions and perceptions regarding self-driving cars vary greatly, meaning those individuals' behaviors around self-driving car are likely to be similarly varied. And though current research has provided great detail on the interaction of autonomous vehicles and their passengers, it has failed to provide an adequate description of the interactions between human operated vehicles and autonomous vehicles. This research gap includes the effect of autonomous vehicles' system transparency on those interactions with human drivers, which could very well relate with changes driving behaviors. In this thesis an educational intervention will be used to communicate details of autonomous vehicles' operations and the decision-making processes that lead to those operations. This clarification in the "how" aspect of autonomous vehicles' intentional model (Lyons, 2013) should increase the system transparency of autonomous vehicles and appropriately calibrate the levels of trust drivers have in them. It is hypothesized that, due to the educational intervention, increased levels of system transparency and trust calibration will lead to significantly different self-reported driving behaviors, with trust positively correlating with participants' autonomous vehicle knowledge scores after the educational intervention.

This hypothesis assumes that current autonomous vehicles are lacking in system transparency, and the drivers who interact with them have inappropriately calibrated levels of trust, leading to inaccurate shared mental models.

CHAPTER 3

METHODS

Design

A survey was administered online via Qualtrics using a repeated-measures design. This method allows the researchers to reach more participants given time and funding constraints.

Participants

Participants were recruited using Amazon's Mechanical Turk (M-Turk) online subject pool. Multiple batches were collected at varying times over multiple days, resulting in 200 participants' data being collected. Of the 200 participants who completed the survey, 151 participants' data could not be used for analysis because their differences between pre- and post-tests to check for learning were small and not significant indicating that they had not read the materials thoroughly. Participants were not excluded based on race, ethnicity, or gender. All participants resided in the United States in order to ensure that participants spoke English and could receive payment in U.S. dollars. Of the 49 participants included for analysis, ages ranged from 18 to 55 years. Other online participant recruitment standards were upheld, such that participants must have 95% completion rate with over 500 completed tests prior, which helped to ensure participants taking the survey were reliable.

Measures

Trust

In order to measure trust, a 10-item scale derived from Jian, Bisantz, and Drury (2000) was utilized. This scale has been validated and is reliable in measuring overall trust in a system. The Jian et al. (2000) trust scale features 10 responses reported on a 7-point Likert scale ranging from "not at all agree" to "extremely agree". Five of these items have a negative connotation in relation to trust (e.g. "I am wary of autonomous vehicles") and thus must be coded accordingly when calculating an overall trust score.

Driving Behaviors

A subset of the Driving Behavior Survey (DBS) developed by Clapp et al. (2010) was used to measure participants' self-reported driving behaviors. After reviewing the three subsets of the DBS, the Exaggerated Safety/Caution Behavior Scale was chosen because it specifically related human drivers (participants) to other drivers (autonomous vehicles) and reflected changes in the participants driving behavior, not aggressive communication to other drivers, which would be not as applicable to the autonomous vehicle context. This scale contained seven items which were rated on a seven-point Likert scale in terms of how likely a participant was to perform the action described, ranging from "not at all likely" to "extremely likely". Using the responses to these seven items, a composite score was created to describe the amount of exaggerated safety/caution driving behavior shown in participants' self-reported data. A higher score represents a higher level of exaggerated safety/caution driving behaviors (maximum score of 49), while a lower score is representative of a lower level of exaggerated safety/caution behaviors (minimum score of 0).

Autonomous Vehicle Educational Intervention

An educational intervention was used to provide participants a baseline understanding of how automation and autonomous vehicles work. The educational intervention facilitates transparency regarding autonomous vehicles and how they operate. This educational intervention (Appendix A) focuses on the systems that autonomous vehicles use to navigate the world (LiDAR, machine learning, etc.). Because there was no way to determine the magnitude of priming from other sources regarding autonomous vehicles (i.e. case studies or new articles), the educational intervention was designed based on factual information about how autonomous vehicles function. This included an explanation of the different levels of automation, what LIDAR is and how autonomous vehicles use it, how autonomous vehicles use other tools like cameras, GPS, and radar for navigation, and finally, how autonomous vehicle manufacturers are using machine learning to allow autonomous vehicles to interpret situations and make decisions on their own. This factual information was included in order to create a more accurate shared mental model of autonomous vehicles, based on research by Ososky, Schuster, Phillips, and Jentsch (2013), explaining how the understanding of the system, including how it operates, its capabilities, and its limitations can help create accurate shared mental models. There were pre- and post-tests regarding the information in the educational intervention, and if participants were not able to score at least a 60% or higher, on the post-test, along with some level of improvement from the pe-test, then their data were not used for analysis. This was to ensure participants were paying attention to the survey, and being effectively educated on autonomous vehicles. The knowledge test (See Appendix A) consisted of five questions, administered both before and after the educational intervention, which were pulled directly from the wording of the intervention.

Procedure

Prior to starting the survey, participants were given a written consent form with information about the study, researcher contact information, opportunity to withdraw at any time, and a choice to agree or not to the study as well as other standard consent form inclusions. The study and all materials were approved by the Institutional Review Board prior to the conduction of 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 et al. (2000) trust scale, the Driving Behavior Survey, and the Positive and Negative Affect Schedule. The Positive and Negative Affect Schedule was a part of another student's thesis project and thus will not be analyzed for this study. Participants filled out all of 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. After completing the post-test, participants were asked to fill out a section which assessed whether they had a driver's license or not, familiarity with autonomous vehicles, and common demographic questions. Again, only participants who scored at least 60% on the post test and showed a score improvement from the pre-test to the post-test were used for data analysis, leaving 49 participants for analysis. The reason for this limitation in usable data is that the working hypothesis predicts that those participants who gain an enhanced understanding of autonomous vehicles will experience a change in driving behavior. Limiting usable data to only those participants who showed an improvement in knowledge check scores ensured that only participants who were affected by the educational intervention are considered for analyses. In addition, limiting usable data to only those participants who scored a 60% or higher on the post-test helped to ensure two things: that participants actually read the material (and didn't guess one or two correct answers to the knowledge check) and that only those participants who remembered a satisfactory amount of the information about autonomous vehicles were considered for analyses. On this topic, Gentile and Lalley (2003) discuss adequate learning in the context of forgetting and concluded that, "If it is less than 60%, it is questionable to speak of forgetting at all, because learning was inadequate in the first place." Furthermore, the purpose of this study is to examine whether or not an enhanced understanding of autonomous vehicles contributes to a change in driving behavior, not to examine the effectiveness of the educational intervention itself.

CHAPTER 4

RESULTS

A paired-samples t-test was conducted to compare Driving Behavior Survey scores in the Pre-Educational Intervention (Pre E.I.) and Post-Educational Intervention (Post E.I.) conditions. There was a significant difference in the scores for the Pre E.I. (M=26.35, SD=11.56) and Post E.I. (M=27.88, SD=12.27) conditions; $t(48)=-2.55$, p =.014. These results indicated a significant change, a small increase, in exaggerated safety/caution behavior in participants' self-reported driving behaviors from the pre-test to the post-test, as shown in Figure 1. Driving Behavior Survey scores are measured on a scale of 0 – 49, with higher scores indicating higher levels of exaggerated safety/caution behaviors.

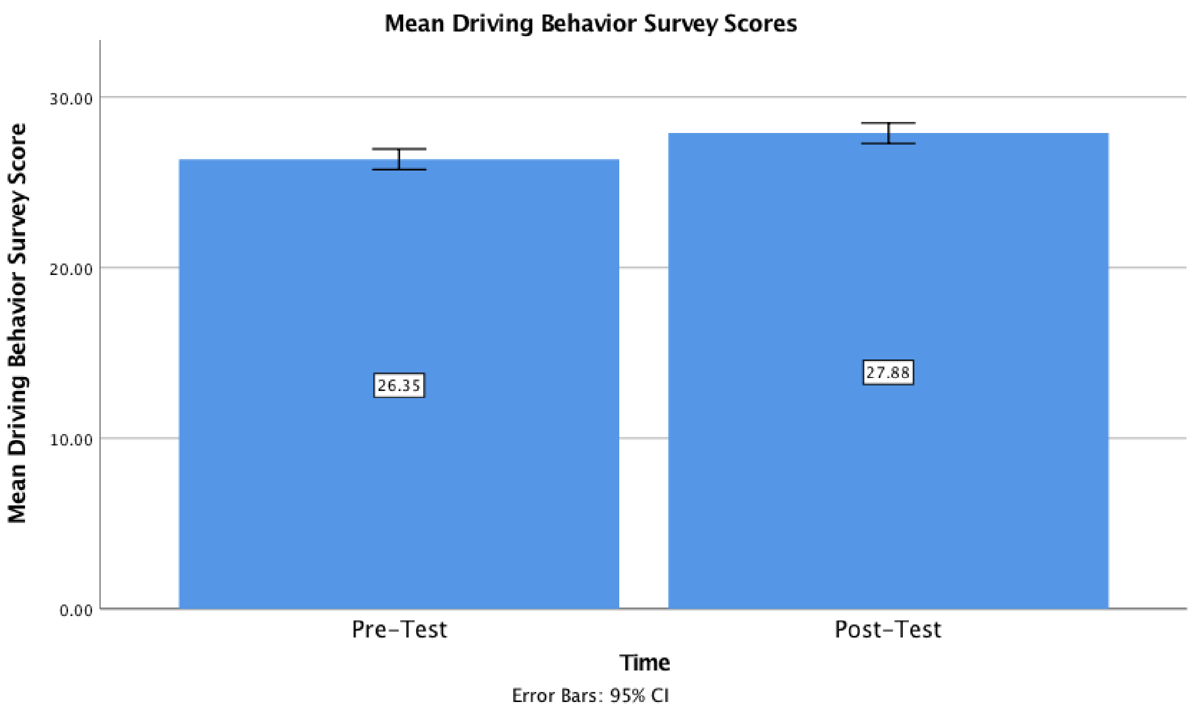

Figure 1

As predicted, a significant change was found in self-reported driving behaviors; the next step was to examine the if the degree of change in reported driving behaviors was related to the degree of change in scores on the educational intervention's knowledge check. A Pearson correlation was performed to measure the relationship between the difference in Driving Behavior Survey scores and the improvement in knowledge check scores, revealing no significant correlation ($r(49)=.19$, $p>.05$). There were only three possible values for the knowledge check improvement variable (one, two, or three), meaning it could be considered a discrete variable, and a Levene's test indicated the homogeneity of variance assumption was met ($p=.35$). Thus, a one-way between- subjects ANOVA was conducted to compare the effect of the change in knowledge check scores on the difference in Driving Behavior Survey scores in three conditions: a one question improvement from the pre test to post test, a two question improvement from pre test to post test, and a three question improvement (the largest improvement measured) from pretest to post test. There was not a significant effect of the change in knowledge check scores on the difference in Driving Behavior Survey scores at the $p<.05$ level for the three conditions [$F(2, 46) = 2.44$, $p = .099$, $\eta_p2 = 0.10$]. The partial eta squared figure shows that approximately 10% of variance in knowledge check improvement is attributable to the educational intervention. The relatively small effect size indicates that non-significance may be attributable in part to an insufficient number of participants.

Table 1

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Pre Jian Trust	49	22	84	63.49	14.55
Post Jian Trust	49	12	84	64.06	14.74
Pre Driving Behavior Survey	49	7	49	26.35	11.56
Post Driving Behavior Survey	49	7	49	27.88	12.27
Pre Knowledge Check	49	0%	40%	30.61%	12.98%
Post Knowledge Check	49	60%	60%	60.00%	0.00%
Valid N (listwise)	49				

Another paired samples t-test was conducted on the participants' pre (M=63.49, SD=14.55) and post (M=64.06, SD=14.74) educational intervention trust scores, which indicated no significant change in trust scores; $t(48)=-.73$, p=.47. A Pearson correlation was performed on improvement in the knowledge check and change in scores on the Jian trust scale, which revealed no significant correlation, [r=.059, n=49, p=.69]. This indicates that, despite limiting the pool of usable data to participant that showed an improvement on the education intervention knowledge check, improvements in participants' understanding of autonomous vehicles had no observable effect on trust scores.

CHAPTER5

DISCUSSION

The purpose of this survey was to determine the effects of an educational intervention about autonomous vehicles on participants' self-reported driving behaviors and whether or not trust positively correlated with scores on the knowledge check of the educational intervention. The above findings indicate that a significant change occurred in self-reported driving behaviors, with participants reporting slightly higher exaggerated safety/caution behaviors, and the null hypothesis is therefore rejected. However, there was not a significant effect of the change in knowledge check scores on the difference in Driving Behavior Survey scores. This result could be attributed to inadequate power after the removal of 151 participants' data, leading to a small effect size. Another possibility is that the education intervention about autonomous vehicles was not effective enough to reconcile system transparency to an appropriate level. Yet another possible cause of this outcome is a failure of the educational intervention's knowledge check to accurately and precisely measure participants' learning.

As shown in the Pearson correlation above, no relationship was found between the change in scores on the Jian trust scale and improvements on the educational intervention knowledge check, therefore the null hypothesis is accepted. Furthermore, results showed no significant change in trust scores between the pre-test and post-test. As mentioned above in driving behavior findings, this lack of change in trust could be due to inadequate power, considering less than a quarter of collected data was considered usable. It is also entirely possible that the educational intervention itself was not effective in improving system transparency, an integral part of trust, which may also help to explain its lack of effect on driving behaviors. The alarmingly low percentage of usable data, classified by a post knowledge check score of 60% and some level of improvement from the pre-test, also points towards either an ineffective educational intervention, or a lack of sensitivity in the knowledge check itself.

Limitations

The limitations of the current study stem mainly from the method of data collection, an online survey, and the lack of proven validity for the educational intervention's knowledge check, because it was created by the researchers exclusively for the purposes of this study. The primary weakness of the online study is the lack of assurance that participants thoroughly read the materials they were presented with. Because this study relies on participants becoming more educated about autonomous vehicles, it is essential that participants take their time and read critically, but due to the lack of a moderator, the best way to ensure this was to institute the limitations on usable data. But merely ensuring that participants improve their knowledge check scores by one question from the pre-test to post-test and score a minimum of 60% on the post-test is not enough to ensure that participants were actually educated about autonomous vehicles. Rather, this limitation of usable data as well as the time limits instituted on the page containing the educational intervention served mainly to help filter out MTurk users whose sole aim was to move through the study as quickly as possible and collect compensation. MTurk creates participant pools in a way that assists participants in maximizing the amount of money that can be made in a given time; though it is a convenient feature for users, it also amplifies the issue of participants doing the bare minimum to collect compensation. A recommendation for any replications or iterations of this study is to change the data collection method to a moderated in-person study. This method's benefits are threefold: it would allow participants to have a resource with which they can clarify questions and comprehension issues, deepening their understanding of the material, it would allow researchers a resource to better ensure that participants make the effort to thoroughly and critically read the materials they are presented with, and it would afford the opportunity to ensure that participants hold valid driver's licenses without compromising their anonymity. It is also important to consider that other extenuating, uncontrollable factors, such as mood changes and fatigue, could have contributed to the observed change in driving behavior. These subject variables make it difficult to determine whether changes in driving behavior can be attributed to the educational intervention or not. Another important change in study design would be the addition of a power analysis to pinpoint the number of participants necessary for the study.

The educational intervention and its corresponding knowledge check should both be considered significant limitations of the study. The design of the education intervention itself was limited by the fact that it had to be presented to participants in text format, and that the information contained within it had to be able to be realistically read in under three minutes. These design constraints limited both the type and amount of information that could be presented. It is obvious that more information is likely to lead to more learning, but, it has also been proven that the implementation of multimedia in learning can lead to accelerated learning, enhanced retention and application of knowledge, and better system understanding (Shank, 2005). The use of a video based, rather than text based, educational intervention could provide users with the enhanced learning effects described above while also providing more information in the same amount of time, if not less. The application of a more informational, video based educational intervention could also allow for a broader and more in-depth knowledge check, accompanied by a higher expectation of participant learning. A quantitative measure for appropriately calibrated trust would also be necessary in order to relate the educational intervention to an improvement in the calibration of trust (this study aimed to create a better mental model, which research suggests contributes to an improvement in calibration of trust).

A final weakness of the current survey is the limitations of the measures it uses, which rely on self-reported data. The Driving Behavior Survey was not created for this study, but adapted for its purposes, meaning that not all of the questions it contains are perfectly applicable to this study. The questions contained in the post test failed to specifically ask participants to consider the new information they had been given in the educational intervention, as they were identical to the questions asked in the pre test. Without specifically asking participants to consider the information presented to them in the educational intervention, they may have felt inclined to answer post test questions similarly, or identically, to the pre test. In addition to these limitations, and the widespread limitations of self-reported data, these measures can only assess participants responses to specific, out of context scenarios. Without the context, emotion, and stakes of a real-life situation, it is impossible to determine the accuracy of a participant's self-reported behaviors. The solution to this issue would be to conduct an experiment using a driving simulator or high-fidelity testbed, which would serve to increase the stakes of the situation while elimination the need for reliance on self-reported data.

CHAPTER 6

CONCLUSION

The results of this study will contribute to future research in the sparsely studied area of the effects of autonomous vehicles on secondary users, such as other drivers, and to the design and implementation of autonomous vehicles themselves. The lack of significant relation between knowledge change and driving behavior change can likely be attributed to the limitations mentioned above, and despite that, a significant change was measured in driving behavior, which is promising. It is also worth considering that this change was indicative of increased exaggerated safety/caution behavior, which is considered a subset of anxious driving behavior. This combination of findings points to the need for further research, albeit with an improved study design to minimize limitations.

This study's findings notwithstanding, the lack of research on autonomous vehicles' effects of the driving environment are startling. The institution of autonomous vehicles into the transportation system en masse is imminent, and yet, its implications are considered in a narrow window typically reserved for pedestrians who will have to interact with autonomous vehicles, and the passengers of those autonomous vehicles. This study is exploratory in nature, with its primary intent being to inform future research on these sparsely studied topics. Experimental testbeds that are able to create higher fidelity scenarios hold the key to finding the full reach of implications autonomous vehicles will have on our world. By implementing studies in which drivers can more readily relate to real world experiences, high fidelity experimental testbeds will be able to paint a more vivid picture of what consequences future mixed autonomy driving environments will have on us.

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APPENDIX A

CHART SURVEY

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	○	○	○	○	○
Distressed	○	○	○	○	○
Excited	○	○	○	○	○
Upset	○	○	○	○	○
Strong	○	○	○	○	○
Guilty	○	○	○	○	○
Scared	○	○	○	○	○
Hostile	○	○	○	○	○
Enthusiastic	○	○	○	○	○
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 behavior

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 behavior

Start of Block: Autonomous Vehicle Knowledge Check

X→

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

---

X→

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

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

---

X→

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

APPENDIX B

IRB EXEMPTION

EXEMPTION GRANTED

Nancy Cooke
Human Systems Engineering (HSE)
480/727-5158
Nancy.Cooke@asu.edu

Dear Nancy Cooke:

On 3/5/2019 the ASU IRB reviewed the following protocol:

Type of Review:	Initial Study
Title:	The Effects of an Educational Intervention on Trust, Positive and Negative Affect, and Driving Behavior around Autonomous Vehicles
Investigator:	Nancy Cooke
IRB ID:	STUDY00009756
Funding:	None
Grant Title:	None
Grant ID:	None
Documents Reviewed:	• InformedConsent (1).pdf, Category: Consent Form; • CHART_Survey_-_2019.pdf, Category: Measures (Survey questions/Interview questions /interview guides/focus group questions); • IRBThesis_Martin_Reagan (1).docx, Category: IRB Protocol;

The IRB determined that the protocol is considered exempt pursuant to Federal Regulations 45CFR46 (2) Tests, surveys, interviews, or observation on 3/5/2019.

In conducting this protocol you are required to follow the requirements listed in the INVESTIGATOR MANUAL (HRP-103).

Sincerely,

IRB Administrator

cc: Sterling Martin
Taylor Reagan
Nancy Cooke