Investigating drivers' trust in autonomous vehicles' decisions of lane changing events

Jackie Ayoub, Feng Zhou
University of Michigan Dearborn, USA

It is potential to improve the interaction between autonomous vehicles (AVs) and drivers by calibrating drivers' trust in AVs. In this study, we investigated drivers' trust in AVs' decisions of changing lanes on a six-lane highway. We derived the AV lane changing scenarios using a machine learning model. The scenarios were rated by 250 participants recruited from Amazon Mechanical Turks (AMTs) in a survey study. The study was designed as a mixed-subject design where the between-subject variable was the amount of information presented (i.e., 3, 4, 5, 6, 7 pieces of information) and the within-subject variable was the information display format (i.e., tabular or visual forms). The results showed that 1) mental demand was always lower in the visual display compared to the tabular one, 2) trust and risk seemed to be inversely proportional across conditions, and 3) 4, 5, or 6 pieces of information tended to be preferred better than others. These results provide design implications on calibrating trust in AV systems by involving the driver in the decision-making process.

INTRODUCTION

Each year more than 1.2 million people died from road accidents (World Health Organization, 2015) and more than 90% of these crashes were caused by human error (Singh, 2015). In order to reduce the numbers of accidents, the AV technology was reported to be promising (Xu et al., 2017). Litman (2015) predicted that by 2050 AVs would be affordable for middle-class people and between 2040 and 2060, the impact of AVs on decreasing road accidents and traffic would start to appear. Even though many of today's vehicles include semi-autonomous features which are considered as the building blocks for AV acceptance, the public does not seem to be ready yet. Moreover, Schoettle & Sivak (2014) showed that the participants had high expectations about AV technology, but they were still concerned about their interaction with the system.

One of the most important factors that influence acceptance of AVs is trust. Recent Uber's and Tesla's AV crashes have shaken consumers' trust in the safety of the system. This was reflected in the recent survey conducted by AAA where they showed that three out of four Americans were still afraid of using AVs (Edmonds, 2019). Shariff et al. (2017) argued that the major roadblocks against adopting AVs are psychological rather than technological. The main psychological barrier is the lack of public trust. Trust can be defined as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" (Lee & See, 2004). According to this definition, the factors that can influence trust in automation are the closed-loop dynamic of reliance and trust, the effect of information display on establishing trust, and adjusting the effect of trust based on reliance. Moreover, Ayoub et al. (2019) summarized the factors affecting trust in AVs into three categories, including 1) human-related factors (i.e., culture, age, gender, experience, and knowledge about AVs), 2) automation-related factors (i.e., reliability, uncertainty, workload, and user interface), and 3) environmental-related factors (i.e., risk, brand). First, for the human-related factors, Hoff & Bashir (2015) showed that they can gradually change overtime due to individual differences. Therefore, to improve people's trust in AVs, designers need to adapt individual preferences in their design. Second, for the automation-related factors, workload has shown to affect the trusting behavior, i.e., the higher the workload, the less the level of reliance and trust in the automation system (Sanchez et al., 2004). Third, for the environmental factors, risk plays a major role in building trust, i.e., the lower the risk, the greater the reliance on automation (Ezer et al., 2008).

To build trust in the AV system, Lee et al. (2016) suggested that the system should share with the driver a continuous evaluation of its performance, information about the external and internal situation of the vehicle, and an emotional interaction. In addition, Khastgir et al. (2018), Shariff et al. (2017), and Dikmen & Burns (2017) showed that trust in AVs were increased with the introduction of knowledge about the limitations and capabilities of the AV system. Another solution to calibrate trust was to communicate the AV decision with the driver in a dynamic manner through a human-machine interface (Khastgir et al., 2018). For a better understanding of trust in automated driving, we conducted a study to investigate the effect of the amount and display format of information on the AV lane changing decisions. Accordingly, we measured the following variables related to the lane changing decisions:1) the risk level, 2) the trust level, 3) the mental demand, and 4) the preferred pieces of information related to the lane changing decisions. The objectives of this study are summarized as follows:

1) Examine the effect of the amount of information presented to drivers on their mental demand, degree of trust, and risk associated with the system decisions.
2) Investigate the effect of the display format, i.e., visual vs. tabular on drivers' mental demand, degree of trust, and risk associated with the system decisions.

METHOD

Participants

A total number of 250 participants (91 females and 159 males) located in the United States participated in this study. The age distribution of the participants was as follows: 48.4% were between 25-34, 20.8 % were between 35-44, 10.8% were between 45-54, 9.2 % were between 18-24, 8.8% were between 55-64, and 2% were above 65. All the participants had a valid US driver's license and they were compensated with $2 upon completion of the survey. The average completion time of the survey was 13.1 minutes.

Apparatus

An online survey was conducted using Amazon Mechanical Turks (AMTs) (Seattle, WA, www.mturk.com/). AMT is a web-based survey company, operated by Amazon Web Services, which has recently become popular in fast data collection (Paolacci et al., 2010). The questionnaire was developed in Qualtrics (Provo, UT, www.qualtrics.com/), a web-based software platform to create surveys. By integrating Qualtrics with AMT, we were able to control the quality of participants, manage their responses, and pay them easily.

Experiment design

Independent variables. In this experiment, we used a mixed-subject design. The between-subject variable was the amount of information presented to the participant based on which the system has predicted the lane change direction. The within-subject variable was the display format used to present the information, either in a visual or a tabular form.

Dependent variables. Based on the amount of information presented to the participants, we measured their level of trust in the system's decision, the level of risk of the situation, and the mental demand level needed to understand the situation. In addition, participants were required to state their preferred amount of information.

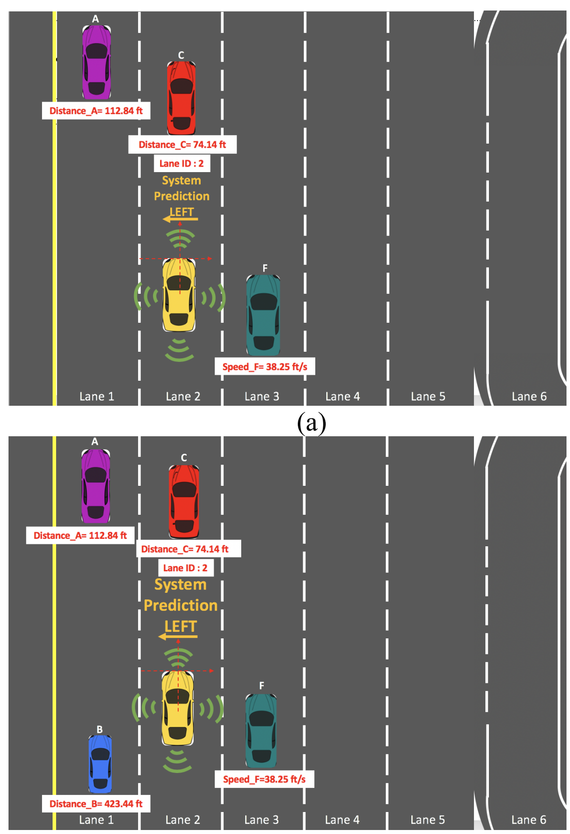
A 7-point Likert scale allowed participants to express their level of trust, level of risk, and required level of mental demand to assess the given information (1 = extremely low, 2 = moderately low, 3 = slightly low, 4 = neither low nor high, 5 = slightly high, 6 = moderately high, 7 = extremely high). The survey consisted of 40 questions, including 20 questions with information regarding the surrounding vehicles presented in a tabular form and another 20 questions with the same information presented in a visual form. Questions were randomized in both visual and tabular forms. For each condition in different pieces of information (i.e., 3, 4, 5, 6, 7), the survey was completed by 50 participants. The order of display format was counterbalanced, i.e., half of the participants saw tabular information first and the other half saw visual information first.

Procedure

Each participant went through the 5 sections of the survey. The first section included a consent form describing the purpose of the study. In the second section, participants filled out a set of demographic questions. The participants were trained to understand and analyze the given information in the survey in the third section. First, they were given detailed explanations about the variables involved in the lane changing scenarios, such as distance, speed, and land ID. Then, the participants were practiced with two example questions, including one with the tabular format and another with the visual format. They were trained on how to think like a passenger in order to reasonably answer these questions. In the fourth and fifth sections, participants were required to answer 40 questions both in a tabular (20 questions) and a visual (20 questions) form with counterbalancing. Each question was on a separate page in order to track participants' timing in answering the questions.

Lane changing scenarios

The Next Generation Simulation (NGSIM) data (NGSIM-Data Portal, 2017) was used in this study to train and test a random forest model (Goel et al., 2017) to predict lane changing events. The NGSIM data included detailed trajectory information of vehicles on the road, such as information about their position and location relative to other vehicles. After cleaning and organizing the raw data, we identified information regarding the ego vehicle and its surrounding vehicles during lane changing events. Based on the collected information, we indicated the lane changing direction of the ego vehicle.



(b)

Figure 1. Visual display of a) 4 pieces of information b) 5 pieces of information

Next, we trained a random forest classifier to predict the lane changing events (F1 score = 0.98, Accuracy = 0.99 with 80% training and 20% testing). In order to understand how the model made prediction of lane changing, LIME (Local Interpretable Model-agnostic Explanations) was used. LIME is an algorithm that explains the prediction of a classifier by approximating it locally (Ribeiro et al., 2016).

Table 1. Tabular display of 4 pieces of information and 5 pieces of information

Distance Leader Left	112.84 ft
Distance Leader	74.14 ft
Leader ID	2
Speed Follower Right	38.25 ft/s

Distance Leader Left	112.84 ft
Distance Leader	74.14 ft
Leader ID	2
Speed Follower Right	38.25 ft/s
Distance Follower Left	423.44 ft

We varied the number of pieces of information between 3 and 7 to obtain the driving scenarios for the survey. We chose 3 as our lower limit because at least this amount of information is needed in lane changing. For example, when changing lanes to the right, we need to know information of the leader on the right, the follower on the right, and the leading vehicles ahead of the ego vehicle. We chose 7 as our maximum limit according to Miller's law (Miller, 1956), where the average maximum amount of information that a person could hold in his/her working memory was about 7.

A visual display of 4 and 5 pieces of information is shown in Figure 1 (a) and Figure 1 (b), respectively. In Figure 1 (a), the yellow vehicle represented the AV that was predicted to turn left based on four pieces of information. The given information included the distance of the leader vehicle on the left (i.e., purple vehicle), the speed of the follower vehicle on the right (i.e., green vehicle), the distance of the leader vehicle (i.e., red vehicle) with respect to the AV, and the lane identification of the AV (i.e., lane ID 2). The tabular display of 4 and 5 pieces of information is shown in Table 1. The difference between 4 and 5 pieces of information is the addition of the distance of the follower on the left. We identified the scenarios using the random forest model with 7 pieces of information, and the scenarios with 6, 5, 4, and 3 pieces of information were derived by deleting one piece of information from the 7 pieces.

Data analysis

We set a time threshold that the participants took to finish the survey to remove participants' data when it was below the threshold. This is because the time each participant took indicates their seriousness in taking the survey and by setting this threshold, we can improve the reliability of the results. Assuming the median value of the $i-th$ participant to finish the survey of the 40 questions in the visual and tabular format is t_{ij} for j $(3 \leq j \leq 7)$ pieces of information. The threshold was empirically set as $mean\ (t_{ij}) - std(t_{ij})$, i.e., the mean value of t_{ij} subtracted by one standard deviation of t_{ij} within the condition of j pieces of information. After data cleaning, the number of participants for each condition is shown in Table 2. A two-way mixed ANOVA model was used to analyze the results with a significance level of $\alpha = 0.05$. Post-hoc analysis was used with Tukey HSD correction.

Table 2. Number of participants for each in each condition after data cleaning

Amount of Information	3	4	5	6	7
Number of Participants	41	40	40	33	36

RESULTS

Table 3 summarizes the mean and standard error of mental demand, risk, and trust for different pieces of information and display formats. Table 4 summarizes the preferred amount of information for the different display formats.

Table 3. Mean and SE of mental demand, risk, and trust for different amount of information and display formats

Amount of Information		**3**	**4**	**5**	**6**	**7**
Mental Demand	Tabular	4.03± 0.22	4.06± 0.21	4.22± 0.23	4.81± 0.25	4.42± 0.27
	Visual	3.31± 0.26	3.62± 0.28	3.42± 0.23	4.00± 0.33	4.10± 0.30
Risk	Tabular	4.10± 0.17	4.27± 0.15	4.20± 0.16	4.51± 0.21	4.64± 0.21
	Visual	3.68± 0.18	4.04± 0.17	4.47± 0.15	4.69± 0.17	5.00± 0.17
Trust	Tabular	4.33± 0.18	4.23± 0.18	4.11± 0.18	4.90± 0.20	4.91± 0.20
	Visual	4.74± 0.17	4.59± 0.17	3.97± 0.17	4.72± 0.19	4.64± 0.21

Table 4. Preferred amount of information for different display formats

Amount of Information		**3**	**4**	**5**	**6**	**7**
Preferred Amount of Information	Tabular	24	43	40	48	35
	Visual	31	40	45	45	29

Mental demand

The main effect of the display format was significant on the mental demand ($F(1,185)= 49.73$, $p = .000$) whereas the main effect of amount of information was not significant ($F(1,185)= 1.70$, $p = .151$). Pairwise comparison showed that mental demand was significantly higher when 3 ($p = .000$), 4 ($p = .023$), 5 ($p = .000$), and 6 ($p = .000$) pieces of information were presented in a tabular form than in a visual form as illustrated in Figure 2.

There was no significant interaction effect between the display format and amount of information ($F(4,185) = 1.25$, $p = .288$).

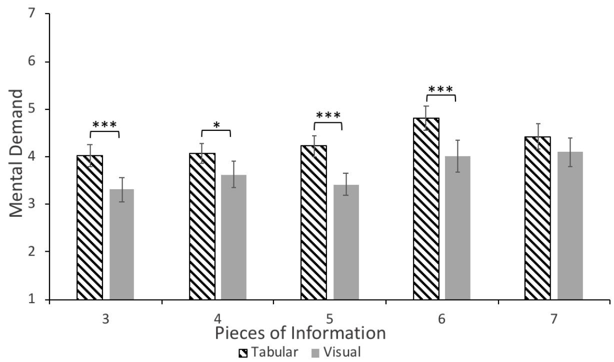


Figure 2. Bar graph depicting the significant effect of the display format and the amount of information on mental demand

Risk

The main effect of display format was not significant ($F(1,185) = 0.23$, $p = .629$). The main effect of amount of information was significant ($F(1,185) = 5.08$, $p = .001$). The pairwise comparison showed a significant difference in the visual form of display between 3 and 5 pieces of information ($p = .008$), 3 and 6 pieces of information ($p = .001$), 3 and 7 pieces of information ($p = .000$), 4 and 7 pieces of information ($p = .001$).

There was a significant interaction between the amount of information and the display format ($F(4,185) = 6.82$, $p = .000$). As illustrated in Figure 3, for 3 ($p = .001$) pieces of information, the risk was higher in the tabular form than in the visual form. However, for 5 ($p = .036$) and 7 ($p = .009$) pieces of information, the risk was higher in the visual form than in the tabular form.

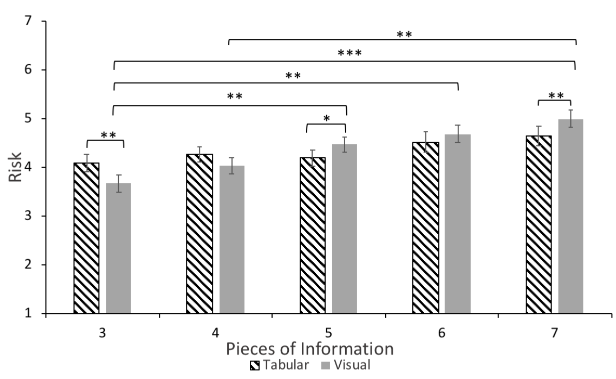


Figure 3. Bar graph depicting the significant effect of the display format and the amount of information on risk

Trust

The main effect of display format was not significant ($F(1,185) = 0.42$, $p = .515$). The main effect of the amount of information was significant ($F(1,185) = 3.14$, $p = .016$). The pairwise comparison showed a significant difference in trust in the visual form of display between 3 and 5 pieces of information ($p = .024$). A significant difference was shown in the tabular form of display between 5 and 6 pieces of information ($p = .048$) and between 5 and 7 pieces of information ($p = .035$).

There was a significant interaction between the amount of information and the display format ($F(4,185) = 6.49$, $p = .000$). As illustrated in Figure 4, for 3 ($p = .001$) and 4 ($p = .004$) pieces of information, the trust was lower in the tabular than in the visual form of display. However, for the 7 ($p = .042$) pieces of information case, the trust was higher in the tabular than in the visual form of display.

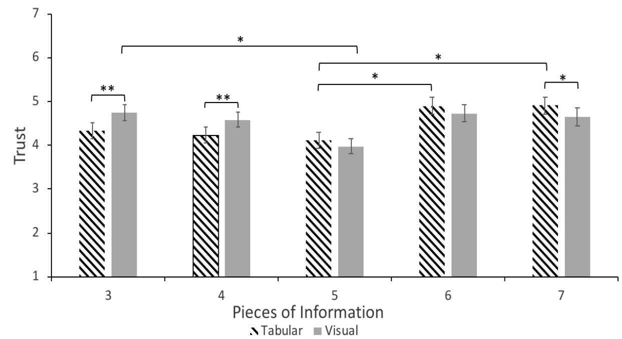


Figure 4. Bar graph depicting the significant effect of the display format and the amount of information on trust

Preferred amount of information

The Chi-squared test did not show any significant difference in participants preference on the different amounts of information displayed in the tabular ($X^2(4,190) = 8.78$, $p = .067$) or the visual format ($X^2(4, 190) = 6.11$, $p = .191$). However, there was a significant main effect when this was done across two display formats ($X^2(4, 380) = 13.21$, $p = .010$). Post-hoc analysis with Turkey HSD correction showed that 5 and 6 pieces of information was significantly preferred than 3 and marginally than 7 and that 4 pieces of information was marginally preferred than 3. From Figure 5, we can see that 4, 5, and 6 pieces of information tended to be better preferred compared to 3 and 7 pieces of information.

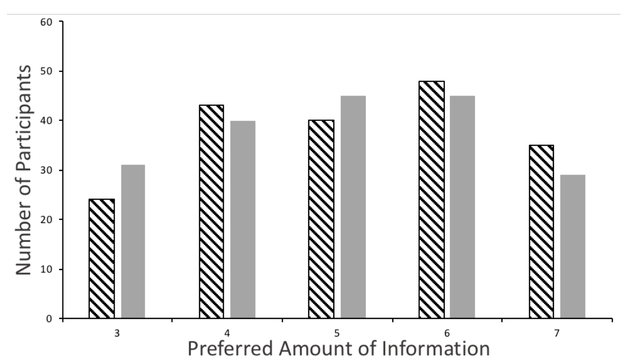


Figure 5. Bar graph depicting participants preferred amount of information

DISCUSSION AND CONCLUSION

This study investigated drivers' trust in AV decisions of making lane changes on a six-lane highway. The lane changing decision was based on information regarding the ego and the surrounding vehicles. We varied the amount of information (i.e., 3, 4, 5, 6, 7 pieces of information) presented to the driver as well as display format (i.e., visual vs. tabular). In order to investigate participants' trust in automated driving in different lane change scenarios, we collected self-reported measures of trust, risk, mental demand, and preferred amount of information.

Consistent with previous studies, the results showed that mental demand was lower in the visual display compared to the tabular one (Shabiralyani et al., 2015). This result was reasonable because the visual encoding can be processed faster in the brain compared to the verbal display. Dewan (2015) showed that visual display was not only effortless to recognize but also faster to recall compared to verbal words. However, there was no significant difference in mental demand between the different amounts of information. With increasing the number of information, we would expect the mental demand to increase, but our study results did not show this trend. This may be due to the fact that the amount of information was a between-subject variable. More research is needed in this aspect.

When less information was presented to participants, the risk level of the decision was lower whereas the trust level was higher in visual compared to tabular displays. When increasing the amount of information, the risk level of the decision was higher in visual displays than in tabular displays. However, the trust level in the visual display was lower than the trust level in the tabular display. Trust and risk seemed to be inversely proportional. Therefore, the risk of the decision decreases when drivers trust the AV performance more. The significant interaction between display format and amount of information on risk and trust might be linked to the mental demand associated with the amount of information provided. However, more insights are needed for future studies to fully understand such results.

As for participants' opinions on their preferred amount of information, participants tended to prefer the middle ranges (i.e., 4-6) to the two extremes (i.e., 3 and 7). Thus, based on the results of the four self-reported measures, we would suggest presenting the system decision to the drivers using 4, 5, or 6 pieces of information displayed in a visual form. Such insights may be helpful to improve the interaction between AVs and drivers. However, it should be cautious that such results may not be conclusive in other situations.

Our study also has several limitations. First, we were not able to capture the seriousness of participants while completing the survey. Additionally, collecting physiological measurements on the participants while filling out the survey can help us in assessing their trust level. Second, the lane changing scenarios were presented in images and tabular forms and thus the information presented may be difficult to understand, especially speed and acceleration, which could potentially influence the results. In the future, the scenarios can be realized with virtual reality with animations to increase its fidelity.

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