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THE INFLUENCE OF RISK ON DRIVER TRUST IN AUTONOMOUS DRIVING SYSTEMS

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ABSTRACT

Autonomous driving systems (ADS) in autonomous and semi-autonomous vehicles have the potential to improve driving safety and enable drivers to perform non-driving tasks concurrently. Drivers sometimes fail to fully leverage a vehicle's autonomy because of a lack of trust. To address this issue, the present study examined the influence of risk on drivers' trust. Subject tests were conducted to evaluate the effects of combined internal and external risk, where participants drove a simulated semi-autonomous vehicle and completed a secondary task at the same time. Results of this study are expected to provide new insights into promoting trust and acceptance of autonomy in both military and civilian settings.

INTRODUCTION

Autonomous driving systems (ADS) now enable drivers to engage in other tasks besides monitoring the vehicle. Autonomous driving can be defined as the ability of a vehicle to drive some distance without human intervention [1]. Autonomous driving allows human operators to fully engage in other important tasks without the need to constantly engage in the driving situation [2]. For example, in a military setting, an important task might include surveillance or mission-critical communications. Fully leveraged, ADS have the potential to make human operators more productive.

The benefits of autonomous driving can never be fully realized unless humans trust ADS. Trust in ADS can be defined as the willingness of human operators to rely on ADS for unsupervised driving, and the reliance on ADS occurs when operators willingly cede control to the automation [3]. More specifically, trust is an attitude toward automation that affects reliance, and reliance is the actual trusting behavior [4]. Unfortunately, drivers often underutilize or refuse to rely on ADS. In this case, drivers either do not hand over control to the vehicle or cannot fully focus on the secondary tasks even if they cede control [2,5]. Trust plays a vital role in understanding driver's unwillingness to rely on ADS and designing countermeasures of the automation [6]. In order to achieve the effective use of the ADS, trust and reliance should maintain an appropriate level over time, such that the ADS can fully function towards an optimal performance in human vehicle cooperation [7-8]. Early stage study on human trust in automation suggested that trust and collaboration efficiency increased constantly with the operators' familiarity of the plant operation, and the size of faults placed a proportional impact on the loss of trust [9]. Lack of trust has the potential to undermine any potential benefits associated with ADS, and an appropriate level of trust is crucial for drivers to understand the capabilities of the ADS as well as adequately monitor the automation [10].

Trust in any system is heavily dependent on the degree of risk associated with the system [11]. Risk – the degree of uncertainty associated with a given situation – is vital to understanding driver's trust and reliance on ADS [12-13]. The use of ADS creates a situation of uncertainty and risk, as smart systems that take over tasks do not work perfectly accurately and can also make errors [14]. To determine the trustworthiness of a teammate, it is crucial that trustor and trustee share the same goal, or trustor can gain adequate knowledge about the behaviors and ability of the trustee, and form senses of high ability, integrity, or benevolence [15]. The form of trusting belief is based on the perceived level of risk, and a lower perceived level of risk leads to higher levels of trust [16]. Research has compared the level of trust to the level of perceived risk measured using 5-Likert scales, and shows that if trust is higher than perceived risk, team members will intend to engage in the risk taking in relationships, otherwise they will be unwilling to engage if perceived risk is higher than trust [15]. Such relationship holds true in human-automation interaction, such as the teaming between the human driver and the ADS [10]. Despite the importance of risk in understanding trust, it is not clear how different types of risk might influence trust and reliance on ADS.

This paper examines the impacts of two types of risk on the trust and reliance on ADS. Internal risk – which refers to the risk arising due to the uncertainty associated with the ADS [17] – was manipulated by varying the reliability of the vehicle alarms. External risk – defined as the uncertainty associated with the driving situation [18] – was manipulated by varying the driving visibility. Several studies have demonstrated the impact of risk on whether humans rely on ADS. Research has shown that increase in internal risk both reduces trust and makes trust more important, and with longer exposure time under risk, the ratings of perceived risk level decrease even though the objective risk level remain high [18]. Also, when the automation proves itself as reliable in recognizing the potential dangers, such as the encountering of vehicles or pedestrians, the drivers tend to trust the ADS more and place more reliance in the ADS [19]. On the contrary, external risk is likely to increase trust and reliance on ADS, as the sense of vulnerability can prompt trust and trusting behaviors of trustors on trustees [14]. For example, we might expect drivers to rely more on ADS in the presence of road sign distractions, fog, etc., with trust in ADS increased as well [20-21]. Research also indicates that driver perceived uncertainty and risk is dependent on trust in ADS, as subjective risk can be reduced by increasing trustworthiness [14]. As such, the research questions we seek to examine are:

- *Q1: Do both internal and external risk moderate the relationship between trust in and the reliance on ADS?*
- *Q2: Is the reliance on ADS positively associated with better task performance?*

To answer these questions, we conducted a human-subject experiment in a simulated driving environment with 36 participants. Participants performed the primary driving task and the secondary target detection task simultaneously. In the experiment, we manipulated two types of risk: internal risk (ADS reliability) and external risk (driving visibility), and measured the primary (e.g., lane keeping, speed, etc.) task performance, the secondary task performance, participants' driving inputs (e.g., steering and braking) and subjective survey responses (e.g., experience in autonomy, perceived trust, risk and workload, etc.). Research also suggested a need to complement survey measures of trust traditionally captured after studies with real-time data [22]. We thus accomplish this by capturing continuous trust measures and physiological measures, such as eye-tracking, heart rate, and skin conductance.

We seek to add to the current knowledge of the impacts of trust in ADS and automated vehicles (AVs), and leverage the results of this study by using the data to help us determine the parameters needed to develop sophisticated and robust models of driver's trust in ADS. Results are expected to inform the design and development of more effective ADS interfaces. The contributions of the paper are as follows:

1. This study contributes to the literature by introducing and exploring the impact of risk on trust in and reliance on ADS.

2. This study examines the combined impact of two different types of risk: internal and external.

METHOD

This study was designed to evaluate driver trust in ADS under different conditions of internal and external risk. This study employs an experimental design with two levels of internal risk (reliability of collision warning system) and two levels of external risk (visibility of the driving environment). These conditions were counterbalanced using a Latin Square design to minimize learning and ordering effects. Participants were asked to operate a simulated vehicle while attending to a visually demanding secondary task. Trust was evaluated from survey responses and analysis of behavioral data.

Participants

Thirty-six licensed drivers were recruited from the Ann Arbor, MI area to participate in the experiment. The average age of participants was 22.74 years old, including fourteen females and twenty-one males, and one chose not to specify. All participants had normal or corrected-to-normal color vision as well as auditory acuity. Participants were paid $15 for their participation and were eligible to receive a cash bonus based on their performance in the experiment.

Tasks

Participants were given the task of operating a simulated semi-autonomous vehicle while attending to a visually-engaging secondary task. The drivers were scored for their performance on both the primary and the secondary tasks in each trial. The best performers in each condition were promised monetary bonuses, which encouraged the subjects to perform their best in all four trials. The simulated vehicle was equipped with lane-keeping, cruise control, and automatic emergency braking. Additionally, the vehicle was equipped with a forward collision warning system that issued verbal alarms when a stopped vehicle appeared in front of the driven vehicle. The alarms were verbal messages: “stopped vehicle ahead” played approximately 8 seconds before reaching each stopped vehicle, followed by either “no action needed” or “take control now” depending on whether the stopped vehicle appeared in the opposite lane or the same lane as the driven vehicle respectively.

Figure 1: Simulated driving view on a standard two-lane divided highway. Vehicle speed and driving mode are displayed in a heads-up display (HUD). A stopped vehicle is placed in front of the ego vehicle as an obstacle.

The primary task for the subjects was to drive the simulated vehicle on the road, while avoiding any collisions. The participants would lose points if they failed to avoid the stopped vehicles. The virtual driving environment consisted of a standard two-lane divided highway with a hard shoulder, as shown in Figure 1, with a stopped vehicle periodically appearing ahead. Two modes could be chosen during the driving, “MANUAL” or “AUTO.” In MANUAL mode, the vehicle could be manually controlled with the steering wheel and the gas and brake pedals, as in a normal car. When AUTO mode was active, the vehicle would maintain its forward speed and stay in its lane without input from user and emergency stops were triggered before the collision with stopped vehicles. Participants were informed that their simulated vehicle was capable of driving itself and delivering alarms, but would not be able to maneuver around a stopped vehicle on the road given the highway speeds. In these circumstances, participants would have to take control of the vehicle by either turning the steering wheel or stepping on the brake.

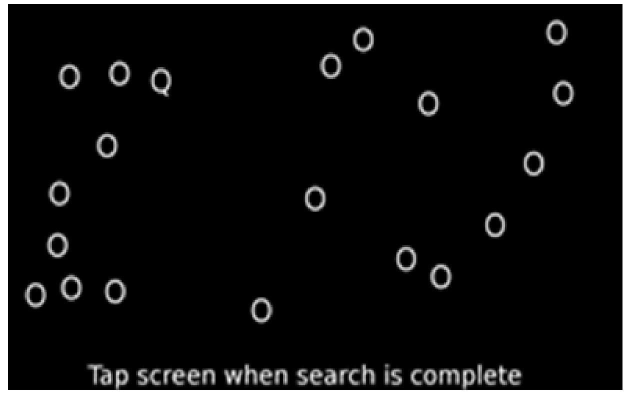

Figure. 2: The visual search task on the touchscreen. This task is administered on a touchscreen and required subjects to manually select the target shape (the letter ‘Q’).

Simultaneously, the subjects need to complete the secondary task. The secondary task was a modified version of the surrogate reference task (SuRT; [23]). The SuRT resembles a target recognition task, as shown in Figure 2, in which subjects must identify a target item (the letter ‘Q’ in this study) from amongst a field of distractors (the letter ‘O’) and manually select it on a touchscreen located to the right of the participant. The goal for the subjects was to correctly identify the targets as fast and as many as possible, for which they would receive points. In the tests, the participants were first shown a target shape, and then a field of shapes including a single instance of the target shape, i.e., a single letter Q amidst O’s. Once subjects located the target shape, they could tap anywhere on the screen. After they tapped, the Q and Os disappeared and were replaced by circles at their corresponding locations. Subjects could then tap the circle corresponding to the location of the target shape.

Each time the participants correctly selected the location of a target shape, they earned one point. And each time they collided into the stopped vehicle, or triggered the emergency stop in the AUTO mode, they lost 25 points. The final scores were recorded to decide the winners who would receive monetary bonus, while simulation data (i.e., vehicle states, take-over behaviors, etc.) and psychological measurements (i.e., GRS, heart rate) were collected for analysis. More details of the collected data and variable are introduced later in the Dependent Variable section.

Apparatus

The study was conducted with a static driving simulator with three visual channels, as shown in Figure 3. Autonomous Navigation Virtual Environment Laboratory [24] is used to create the virtual environment and implement the semi-autonomous driving behavior. PEBL [25] is used to create the non-driving task. The task itself is administered on a touchscreen to the right of the participant where a vehicle's center console would be in an actual vehicle. A head-mounted eye-tracker is used to collect participant gaze behavior during the study. This device captures video of the wearer's field of view and of the wearer's right eye. Galvanic skin response (GSR) and heart rate are also collected during the study.

Figure 3: Driving simulator and secondary task setup. A volunteer is driving with the simulated vehicle while doing visual-search task on a touchscreen. Markers are placed on each monitor and the touchscreen to identify surfaces for eye-tracking.

Independent Variables

The study employed a 2×2 within-subjects design. The two independent variables in this experiment were internal risk and external risk. Internal risk was manipulated via the reliability of the forward collision warning system; external risk was manipulated via the visibility of the road due to fog. Each variable had two levels: low and high, as presented in the table below. Each subject experiences all four combinations, which are shown in Table. 1:

Table. 1

		Internal risk (reliability)	
		Low internal (100% reliable)	High internal (70% reliable)
External risk (visibility)	Low external (high visibility)	Low ext. risk - Low int. risk	Low ext. risk - High int. risk
	High external (low visibility)	High ext. risk - Low int. risk	High ext. risk - High int. risk

Under the low external risk (high visibility) condition, as shown in Figure 4 (a), subjects could see over 1000 feet down the road. Under the high external risk (low visibility) conditions, as shown in Figure 4 (b), subjects could only see about 500 feet down the road. Fog was added to the simulated environment to form a low visibility scenario in the high external risk conditions. The forward collision warning played right before each stopped vehicle appeared in the low visibility conditions, i.e., when the stopped vehicle was 500 feet ahead. Under the low internal risk (high reliability) condition, the forward collision warnings are always correct. Under the high internal risk (low reliability) condition, for 30% of the forward collisions, warnings are false positive alarms. The reliability levels were chosen considering real-life ADS systems and through the feedback from the pilot study. Furthermore, false alarms were placed in the 2nd, the 3rd and the 5th encounters among the total 10 encounters, as studies have shown that trust is affected more by early failures than by later losses of reliability [22].

(a)

(b)

Figure 4: The driving environment with different visibility. (a) High visibility case: visible distance is around 1000 feet, and drivers can see a stopped vehicle ahead 14 sec before reaching it; (b) Low visibility case: visible distance is around 500 feet, and drivers can see a stopped vehicle ahead 7 sec before reaching it.

Dependent Variables

In the experiment, the following dependent variables were measured through the data collection:

The survey responses were collected through pre-experiment and post-experiment surveys, which produced the preliminary results presented in the paper. The pre-experiment surveys measured the demographic and driving experience, the Mood via SAM [26], the driving risk tolerance [27], and the propensity to trust in automation [28]. The post-experiment surveys measured the perceived risk (adapted from [11]), the self-reported trust via Trust in Automation Survey [5], and the workload via NASA TLX [29].

Also, the simulation data and the physiological data were collected during experiment. The simulation data consisted of variables of four categories: the simulated vehicle state, the proximity to the nearest upcoming stopped vehicle, the participant take-over behavior, and the participant secondary task engagement which included scores and reaction time. The physiological data consisted the eye-tracking data with monitoring ratio and monitoring frequency, the heart rate (HR) data, and the galvanic skin response (GSR) data. These variables would be used in future analysis.

Procedure

Participants first completed a consent form to participate in the study. Next, participants completed a pre-experiment survey, which consisted of questions about demographic information as well as experience using driving aids, such as adaptive cruise control and forward collision warning. It also included questions to determine each participant's risk tolerance and propensity to trust in automation.

After completing the pre-experiment survey, participants completed a brief training session to become familiar with the vehicle controls and the secondary task. Following training, the eye-tracker and GSR/heart rate monitor were fitted and calibrated. Participants then completed four test sessions, one corresponding to each of the pairs of internal and external risk levels. Each driving session lasted approximately 10 minutes. At the end of each session, participants completed the post-condition survey. The post-condition survey included measures for perceived risk, trust in automation, and perceived workload. Surveys of 27 subjects were administered via web-form, while the other 11 subjects completed surveys via paper-form due to software constraints. Each experiment lasted approximately 110 minutes.

PRELIMINARY OUTCOMES

In the final results we expect to answer the research questions proposed in the Introduction section. This paper presents the preliminary outcomes regarding the first question, i.e., *Do both internal and external risk moderate the relationship between trust in and the reliance on ADS?*

Analysis has been conducted on the following variables: self-reported trust, reliance, risk, workload in ADS, which were collected from post experiment surveys, and the secondary task performance. The preliminary outcome on self-reported trust is presented in this section. The analysis employs the survey responses of 27 subjects that fulfilled surveys via web-form. The subjective trust scores are shown in Figure 5, each corresponding to one risk condition:

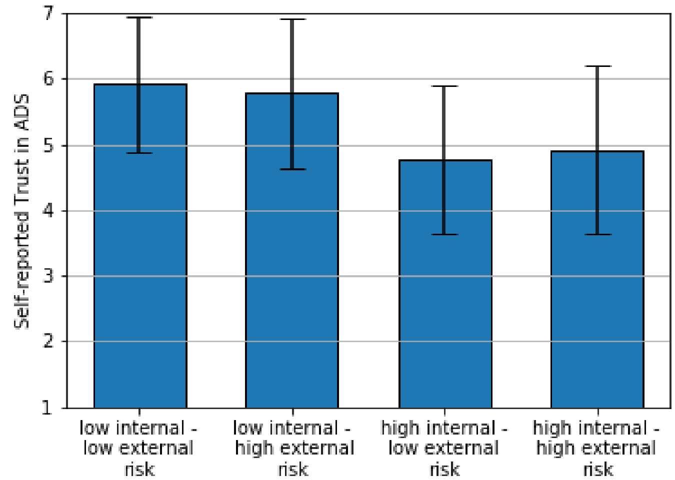

Figure 5: Self-reported driver trust on the ADS. The blue bars show the average trust scores under four combined risk scenarios calculated from the survey responses.

The trust scores for each subject were calculated by averaging self-reported values with five different trust measures on ADS (i.e., competence, predictability, reliability over time, dependability, and responsibility), using the 7-point Likert scale (i.e., score 1 stands for “no trust at all”, and score 7 stands for “complete trust”). The survey questions on system trustworthiness are as follows:

1. Competence: To what extent did the autonomy perform its function properly? In other words, to what extent does the driving autonomy prevent and help prevent collisions and enable safe multi-tasking?

2. Predictability: To what extent can the autonomy’s behavior be predicted from moment to moment?

3. Reliability over Time: To what extent does the autonomy respond similarly when it encounters similar circumstances at different points in time?

4. Dependability: To what extent can you count on the autonomy to do its job?

5. Responsibility: To what extent did the autonomy perform the task it was designed to do? In other words, to what extent does the driving

autonomy drive safely and enable safe multi-tasking?

The scores were collected from the post-experiment surveys taken after each session of subject trials. The histogram is presented with blue bars showing the average of trust scores, and black standard error bars showing the standard deviation.

As indicated in Figure 5, internal risk and external risk have different effects on trust. The results imply that the internal risk (i.e., the reliability of warning system) has a negative influence on trust in the autonomy: when the warning system is unreliable, the drivers tend to trust less in the autonomy. Meanwhile, the impact of external risk (i.e., the visibility of driving environment) is minor compared to internal risk. The results indicate that internal risk reduces trust in ADS. Also, the impact of internal risk appears stronger than external risk. External risk shows minor impact on self-reported trust, which remains to be investigated with other trust measures.

Nevertheless, self-reported trust through questionnaires may not be fully representative of actual trust and trusting behaviors [2,22]. It remains unclear how multiple factors influence the measures simultaneously. Further investigation should be conducted with continuous trust measures and physiological data which might provide a different conclusion.

CONCLUSION

In this study, the combined influence of internal and external risk on driver trust and reliance in the ADS was evaluated. A human-in-the-loop experiment was conducted, where subjects drove a simulated semi-autonomous vehicle under different risk scenarios. The preliminary results on self-reported trust suggest that 1) internal risk reduces trust in ADS, and 2) internal risk has a greater impact on trust than external risk.

FUTURE WORK

For the next step, we will consider the physiological data, simulation data, and use continuous trust measures together with the survey data. Based on the results, we will build a control model for the mutual trust between human operator and the ADS in semi-autonomous driving, which will be able to predict real-time trust intentions corresponding to different conditions. User performance in primary and secondary tasks would also be evaluated and modeled into the automation system. The outcomes of this study will be used to develop ADS with appropriate taking-over or ceding-control behaviors in human-vehicle cooperative driving.

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