When Do Drivers Intervene In Autonomous Driving? Contrasting Drivers’ Perceived Risk Across Two Mobility Types

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ABSTRACT
Autonomous vehicles (AVs) are expected to handle traffic scenarios more safely and efficiently than human drivers. However, it needs to be better understood which AV decisions are perceived to be unsafe or risky by drivers. To investigate drivers’ perceived risk, we conducted a driving simulator experiment where participants are driven around by two types of AVs—car and sidewalk mobility—with a driving style that matches the participant’s driving style. We developed a computational model that allows us to examine drivers’ perceived risk of scenarios when interacting with an AV based on the drivers’ interventions. The model allows us to quantify and compare the relative perceived risk of different scenarios for the two mobility types. Our results indicate that 1) drivers perceived higher risk in scenarios where the AV attempts to match the driver’s preferred driving style, and 2) different scenarios were perceived as having higher risk across the two mobility types. The ability to quantify the perceived risk of scenarios and an understanding of how perceived risk differs across mobility types will provide critical insights for the design of human-aware mobility.

CCS CONCEPTS
• Human-centered computing → Human computer interaction (HCI); Empirical studies in HCI; User models; HCI design and evaluation methods.

KEYWORDS
Autonomous vehicles, perceived risk, trust, car mobility, sidewalk mobility

ACM Reference Format:

1 INTRODUCTION & BACKGROUND
The risk perception of drivers has been extensively researched to enhance safety in transportation. We know that a variety of driver-specific factors such as age [10], experience [9], socio-economic status [14], and personality types [20] affect drivers’ risk perception. While understanding the driver-specific factors influence the subjective perceived risk of mobility users, it is also essential to understand how scenario-specific factors manifest in the drivers’ perception of risk. Furthermore, most previous investigations of risk perception have been limited to car mobility [2, 3, 10, 14]. However, the choices of autonomous mobility types are rapidly evolving. In addition to cars, drivers may soon have access to a variety of semi-autonomous sidewalk mobility types such as e-scooters [22]. Hence it is important to investigate how drivers’ perception of scenarios differs across mobility types. Our work focuses on two questions: 1) which scenarios are generally perceived as high risk by drivers? and 2) how does the type of mobility interact with the risk perception of scenarios? Specifically, we contrast the scenarios perceived as risky when interacting with an autonomous car versus an autonomous sidewalk mobility (such as an e-scooter).

When interacting with an AV, drivers must constantly appraise situational risk and adjust their trust in the AV to make decisions of whether to take over control from the AV or to allow the AV to continue driving. Driver intervention can be interpreted as an indication of a lack of trust, or high perceived risk, or a combination of both. Several studies suggest that drivers tend to trust AVs that drive in a way that resembles their own driving style [7, 17]. In contrast, [12] show that drivers favor defensive AV driving in general. Most previous work attributes a driver’s decision to override the AV to driver-specific traits or AV-specific features. We hypothesize that interventions such as braking by the driver may be influenced by scenario-specific risk in addition to the AV’s driving style and the driver’s trust in the AV. To tease apart the contribution of driver-specific trust and scenario-specific risk, we develop a computational model that infers trust and perceived risk from drivers’ braking behavior.

Trust combined with situational attitudes such as perceived risk modulates drivers’ intention to rely on automation [11]. Both trust and perceived risk are commonly measured in human-subject experiments via surveys, or by intermittently probing participants to indicate their perceived risk of a situation [8, 14]. Instead of using such empirical measures, we directly infer trust and perceived
risk from the intervention behavior of humans being driven by an AV. We posit that a driver’s tendency to intervene in an AV's driving in a given situation depends on two factors: 1) the driver’s trust in the AV’s driving capabilities, and 2) the risk associated with the situation. We develop a model that treats driver trust and scenario-specific perceived risk as latent constructs. This modeling framework provides a principled way to understand which scenarios and AV actions are perceived as risky. It also allows us to examine how risk perception differs across two different kinds of mobility, namely car and sidewalk mobility, where the latter is largely unexplored in the literature. We qualitatively contrast scenarios that are perceived as high risk in the two mobility types.

2 METHODS

2.1 Experiment Setup
We conducted an in-person driving simulator experiment that tasked participants with supervising an AV [16]. Each participant supervised three AV drives across two mobility types: car and sidewalk. The experiment was conducted using a high-fidelity driving simulator based on Unreal Engine 4.24 [5] with AirSim [19] that consisted of a custom city where the automated driving was simulated by replaying a past researcher’s drive via the “Wizard of Oz” technique [24]. The environment was shown to participants using a StarVR headset with a 210-degree FoV. A motion base (MB-200 6-degree of freedom motion base by Cosmate Co., Ltd.) was used to allow for a higher fidelity simulation where participants could feel the typical forces experienced in a vehicle. A car platform was used for all car mobility drives, and a scooter platform was used for all sidewalk mobility drives (see Figure 1).

2.2 Experiment Design

2.2.1 Drive Types. The experiment consists of a tutorial drive, “proactive” drives, and standard drives, all autonomous drives and are described below.

Tutorial drive. The tutorial consisted of a simple drive through an empty urban area with no other cars or pedestrians, which lasted for approximately 3 minutes.

Proactive drives. To manipulate trust without changing automation reliability, a set of events was created in which the automation performed “proactive” maneuvers while maintaining safe driving behavior. The goal of these events was to create situations in which the AV had multiple options for safe actions to perform. For each event, two actions were designed; one represented an “aggressive” action while the other represented a “defensive” action. Table 1 and Figure 2 give examples of proactive scenarios and the AV’s response to these scenarios for both car and sidewalk mobility. Each proactive drive had 8 events and each drive was approximately 12 minutes long. Since all car events were not directly applicable to sidewalk mobility, equivalent events were created to match the car events as closely as possible.

We hypothesize that scenarios where the AV makes proactive decisions would be perceived as high risk by participants. However, we expect that participants would not intervene in the proactive decisions of the AV as the AV’s driving style is matched to the participant’s preferred driving style as described in Section 2.3.

(a) Autonomous car.

(b) Autonomous sidewalk mobility.

Figure 1: Driving simulator setup.

(a) Car event where the car crosses the double yellow line in order to get into the turn lane when there is stopped traffic ahead.

(b) Sidewalk mobility event where the sidewalk mobility drives onto the road outside the crosswalk lines because of stopped pedestrians ahead.

Figure 2: Example proactive car event and sidewalk event. The green arrow shows the path that will be traversed.

Standard drives. Standard drives involved no proactive events in order to serve as prerequisite trust-building drives (prior to proactive drives). They involved the automated vehicle navigating through multiple intersections in an urban area. Similar to proactive drives, standard drives included the presence of other cars and pedestrians throughout the urban area; however, there were
Table 1: Illustrative examples of proactive scenarios and corresponding aggressive and defensive AV decisions for the car and sidewalk mobility.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Car Mobility</th>
<th>Sidewalk Mobility</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yellow light ahead</td>
<td>Aggressive Decision</td>
<td>Yellow light ahead</td>
</tr>
<tr>
<td></td>
<td>Defensive Decision</td>
<td>maintaining speed</td>
</tr>
<tr>
<td></td>
<td></td>
<td>stopping</td>
</tr>
<tr>
<td>Heavy traffic ahead</td>
<td>turning at gap</td>
<td>continuing</td>
</tr>
<tr>
<td>Pedestrians stopped</td>
<td>crossing lines to pass</td>
<td>waiting for safe</td>
</tr>
<tr>
<td>Left turn lane blocked</td>
<td></td>
<td>turn</td>
</tr>
</tbody>
</table>

no ambiguous scenarios that required advanced decision-making by the automated vehicle. Each drive lasted for approximately 8 minutes.

2.2.2 Intervention by drivers. Participants were instructed to monitor the AV’s driving and they could indicate their intent to intervene in the AV’s driving by braking or accelerating for both the car and sidewalk mobility. Braking and accelerating intents were captured using the brake and throttle foot-pedals for the car and the brake and throttle hand-levers for the sidewalk mobility; respectively. Participants were informed that their braking or accelerating intentions would not cause any changes in the drive but it would be used as feedback by the AV.

In our current analysis, we divide each drive into traffic scenarios of ~10s each, and limit our analysis to braking interventions by drivers. We perceive braking as an indication that participants may have realized the limitations of automation or they may not be comfortable with the AV actions. If the driver brakes in the duration of a scenario, then it is considered a braking instance.

2.3 Experiment Procedure

Forty-eight participants recruited from a university campus completed the in-person study at the simulator room in Honda Research Institute’s USA Inc, San Jose. Participants were matched with a defensive or aggressive AV group on a survey: they were asked to choose between two driving videos based on the video’s resemblance to their own driving style. The two videos were designed to recreate aggressive and defensive driving styles. Once the participant was assigned to a defensive or aggressive AV group, the participant was then randomly assigned to monitor an autonomous car or an autonomous sidewalk. For each of the two mobility types, the participant first monitored a tutorial, then saw either 1) a standard drive followed by a proactive drive, or 2) two proactive drives. Participants monitored the two mobility types in two separate sessions conducted 1 hour apart.

This experiment allows for many interesting investigations of drivers’ braking behavior in different drive-type combinations. For instance, comparing braking in standard and proactive drives, or the effect of interacting with one mobility type, say car, before switching to the sidewalk mobility. However, this paper presents preliminary work where we restrict our analyses to drivers’ interaction with the AV in the first proactive drive they monitored.

2.4 Computational Framework: Item Response Theory Model to Infer Risk

An individual taking a risk is considered to be exhibiting behavioral trust [15]. Conversely, braking by a driver may be interpreted as a lack of trust in the AV when faced with a risky scenario. We posit that driver’s intent to brake during any traffic scenario is based on two latent variables: 1) the driver’s trust in the AV’s driving capabilities, and 2) the risk associated with the traffic scenario. While trust is a complex multi-dimensional construct [1], here we model it as one-dimensional – all variations in trust can be characterized by changes along a single overall trust scale.

Our framework is based on the item response theory model (IRT, [6, 23]). Specifically, we use a basic Rasch model [18]. IRT models have been extensively used in the education and cognitive science communities to model performance differences across people and the problems they encounter.

We modify the basic IRT model to account for individual differences in trust and differences in risk associated with traffic scenarios. Let $x_{i,j}$ be a binary indicator of braking by driver $i$ in scenario $j$. We model $x_{i,j}$ by combining two latent factors, the trust $t_i$ of each driver $i$ and the risk $r_j$ associated with situation $j$:

$$
\theta_{i,j} = t_i - r_j
$$

$$
p_{i,j} = \frac{1}{1 + \exp(-\theta_{i,j})}
$$

$$
x_{i,j} \sim \text{Bernoulli}(p_{i,j})
$$

Note that $t_i$ represents an aggregate measure of trust for each driver $i$. The IRT model allows us to rank drivers in order of their exhibited trusting behavior while accounting for the risk $r_j$ associated with each scenario $j$.

For $t_i$, we use a left-skewed normal prior to account for the empirical observation that some drivers never expressed an intention to brake. We posit that drivers who never intended to brake have the highest level of trust in the AV. For risk, $r_j$, we use a standard normal prior to avoid identifiability issues [6]. We used Markov Chain Monte Carlo (MCMC) sampling to infer model parameters and obtain samples from the posterior distribution. We chose the Stan computing environment for posterior inference [21].

3 RESULTS & DISCUSSION

3.1 Perceived Risk in Proactive vs Standard Scenarios

We use the IRT model to infer which events are perceived as having high risk by participants. In Figure 3, we see the distribution of the
inferred risk values for situations where the AV took a proactive decision and for situations where the AV did not take a proactive decision. Higher values on the x-axis correspond to higher perceived risk. For all mobility and driving style combinations, we observe a similar pattern: participants perceived proactive events as having higher risk as compared to standard events.

Most prior research suggests that drivers prefer an AV with a driving style similar to their own [13] or defensive AV driving in general [4]. In line with these previous findings, we expected that participants in our experiment would have fewer braking instances in scenarios where the AV makes a proactive decision. Instead, we observe that both defensive and aggressive proactive actions by the AV lead to high perceived risk and consequently braking by the participants. We posit that participants perceive some scenarios as risky independent of the driving style of the AV. Hence, it is crucial that we account for drivers’ perceived risk in addition to driving style preferences when designing human-aware AV systems.

We used a two-sample Kolmogorov-Smirnov (KS) test to examine if the perceived risk of proactive events is different from the perceived risk of standard events. For both mobility types, and for both aggressive and defensive AVs, the distribution of the perceived risk of proactive scenarios is significantly different from the perceived risk of standard scenarios (Fig. 3 (a) KS statistic = .632, p-value = .005, (b) KS statistic = .572, p-value = .014, (c) KS statistic = .550, p-value = .095, and (d) KS statistic = .679, p-value = .008).

3.2 Perceived Risk in Car vs Sidewalk Mobility
A key feature of our experiment is that participants interacted with two different kinds of mobility types: car and sidewalk mobility. In order to better understand which scenarios are perceived as riskier than others in both these mobility types, we tag the scenarios in all drives as interactions with either pedestrians or cars. For example, if the scenario involves a pedestrian crossing the road then it would be tagged a ‘pedestrian’ scenario. Whereas if the scenario involves the AV waiting at an intersection for other cars to pass then it would be tagged a ‘car’ scenario.

The output from the IRT-based model allows us to qualitatively contrast which scenarios are perceived as having high risk in the two mobility types. Within the scenarios that are inferred as being high-risk by the model, we observe a pattern: when being driven by an autonomous car, participants perceived events involving pedestrians as higher risk when compared to other events, i.e. drivers were highly likely to override the AV and brake when there was a pedestrian around. In contrast, when being driven by the autonomous sidewalk mobility, events that involved cars were perceived as higher risk than other events. This is a key yet intuitive insight from this analysis: which scenarios are perceived as risky depends on the type of mobility.

3.3 Limitations & Future Work
In our future work, we aim to study how perceived risk changes as drivers repeatedly interact with the same AV and in similar traffic scenarios. To do this, we have developed an online version of our experiment that will give us access to a larger participant pool and will allow us to have drivers interact with an AV in multiple drives. Note that while our model captures the perceived risk of scenarios, it does not explain how the perceived risk of scenarios changes over time. One important extension of the current work is to model change in perceived risk when participants are exposed to similar scenarios multiple times.

4 CONCLUSION
We present the first (to our knowledge) assessment of drivers’ risk perception of traffic events across autonomous car and sidewalk mobility. We develop an IRT-based model to infer the perceived risk of traffic scenarios. We use this model to examine the differences in risk associated with scenarios when the AV makes decisions that are in line with the driver’s preferred driving style. We observe a significant difference between drivers’ perceived risk in scenarios where the AV takes a proactive decision as compared to scenarios where the AV takes a standard decision. This difference is consistent across two different mobility types—car and sidewalk.

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