Enhancing Passenger Trust Toward Cooperative Autonomous Vehicles Using Simulated Augmented Reality Displays

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Abstract

Adoption of Fully Autonomous Vehicles (FAVs) depends on trust, which is defined as confidence in a vehicle's dependability, safety, and predictability. In cooperative driving scenarios, trust must exceed ego vehicles to include other autonomous vehicles and their coordination. This is challenged by unexpected multi-agent interactions, diminishing human control, and limited system transparency. We hypothesize that enhancing transparency by providing information about ego vehicle, other cooperative vehicles, and road conditions can foster trust. This is achieved by visualizing vehicle-to-everything (V2X) information via augmented reality (AR) interfaces. To test this in a safe environment, we conducted a within-subjects experiment in a Virtual Reality (VR) driving simulator with AR overlays. Participants experienced three interface concepts: (A) no transparency, (B) system-level transparency (ego vehicle intentions only), and (C) environment-level transparency (cooperation intentions, planned paths, and infrastructure). Results show that environment-level transparency, despite the higher cognitive workload, enhanced trust in both ego and cooperating FAVs.

CCS Concepts

• **Human-centered computing → Empirical studies in HCI**.

Keywords

Autonomous Vehicles, Augmented Reality, Vehicle-to-Everything (V2X), Passenger Trust

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1 Introduction

1.1 Autonomous Vehicles Potential

Fully autonomous vehicles, or FAVs, are considered the future of transportation and are expected to enter the market within this decade [29]. These vehicles have the potential to eliminate human errors, which account for approximately 90% of road accidents [18], while also improving traffic efficiency and reducing fuel consumption by optimizing traffic flow, ultimately leading to shorter travel times and lower travel costs [15]. This technology will also change our driving experience; researchers pointed out that people will be able to do more work or leisure-related activities while traveling [2]. Others demonstrated that drivers use slow-moving traffic to do business-related tasks, splitting their focus between paperwork and mobile phone calls [20].

1.2 Adoption Challenges of Connected Fully Autonomous Vehicles

Despite these benefits, user acceptance is not guaranteed; AVs still need to behave in a way that users can understand and predict. Surveys carried out in the United States have revealed that there is a significant reluctance toward the FAVs [1]. These challenges are expected to evolve as autonomous vehicles reach full autonomy. Research highlighted that the problem of overtrust diminishes, since no human intervention will be required at such levels, but distrust becomes the most critical challenge to address [38].

The next generation of AVs will not only become fully autonomous but also cooperative, engaging in more complex maneuvers such as cooperative lane changes, platooning, and intersection negotiation. [8, 26, 39]. This resembles a swarm of robots operating in coordination to achieve shared goals [3, 26]. While such coordination improves safety and network efficiency [9], it introduces trust challenges by making it more fragile. Researchers highlighted that trust is prone to generalization, especially when a set of robots interact with each other; users might transfer their distrust to the other cooperating agents, resulting in wide trust erosion [37].

In such a configuration, passengers must trust not only their own vehicle but also the behaviors of nearby cooperative agents, where distrust in one vehicle can lead to distrust in others. Despite this, little is known about how interface design can support trust calibration in such multi-agent, cooperative environments. This presents a critical barrier to user acceptance and safe deployment of connected autonomous vehicles.

1.3 Interface Design for Cooperative Autonomy

The objective of this study is to investigate how different interface concepts impact passenger trust toward ego vehicle and cooperative agents, situational awareness, cognitive workload, and technology acceptance in cooperative autonomous vehicle scenarios, using a virtual reality driving simulation. While one interface might enhance user trust, it might result in an increase in cognitive workload, impairing situational awareness, or resulting in a rejection of the technology.

In this paper, we distinguish between information conveyed to the user through their ego vehicle and information received from the environment. The latter includes data from other cooperative agents, infrastructure-related details such as road blockages, and cooperative intentions between the ego vehicle and other agents. We refer to this category as environment-level transparency. Figure 1 shows the difference between each concept.

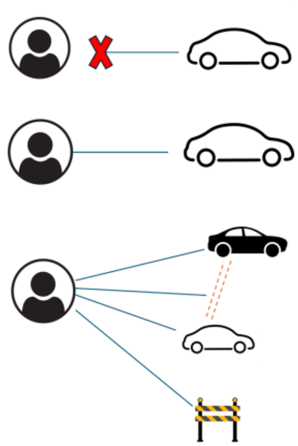

Figure 1: Transparency levels. From top to bottom: (1) No or minimal transparency, where the user receives little to no feedback; (2) System level transparency, where the user receives information from the ego vehicle; (3) Environment level transparency, where the user receives feedback from multiple sources including other vehicles, infrastructure such as road blockages, and shared cooperative intentions.

We carried out a within-subject experiment in a virtual reality-based autonomous vehicle simulator (N=30), utilizing DReyeVR[32]. Participants were exposed to three wearable augmented reality concepts within virtual reality (VR), an approach that was explored by other researchers [24, 27]. Concept A offered minimal transparency, depicting only the speed of the vehicle. Concept B offered system-level transparency based on visualizing the ego vehicle's intentions only. Concept C used environment-level transparency through V2X, with a more specific concentration on V2V and V2I communication, as these encompass the essential information that represents the environment. Participants experienced the interfaces in a balanced Latin square order. Each scenario lasted for 3 minutes, after which participants responded a questionnaire which adapted the Trust in Automation questionnaire to assess trust [16], SART Questionnaire [30] to assess situational awareness, NASA-TLX [12] to evaluate cognitive workload, and Technology Acceptance Model Questionnaire (TAM) [6] to measure overall acceptance.

2 Related Work

2.1 Trust in Automated Systems and the Technology Acceptance Model

Human trust in an automated system can be defined as a multidimensional construct that reflects a user's willingness to rely on an AV based on their expectations regarding a number of performance metrics [14]. Dimensions of trust can be decomposed into multiple factors, each contributing to the user's perception and interaction with the system [16]. These dimensions include perceived reliability, perceived capability, intentionality, understanding, and faith [21]. The user's confidence that the system will function as planned and without error is known as perceived reliability. Perceived capability demonstrates how the user evaluates the system's ability to carry out its duties efficiently. Understanding demonstrates how well the user comprehends the operation and decision-making process of the system. The user's view that system behaviors will perfectly match his goals is indicated by intentionality. Lastly, faith is the firm belief that the system is reliable and has good intentions, even in the absence of total knowledge [21]. This trust is also influenced by cognitive and emotional factors, not just performance metrics [14]. Building on all of these elements, dispositional trust, situational trust, and learned trust are the three main aspects that make up trust. Situational trust is impacted by system complexity, workload, and self-confidence; learned trust grows as familiarity with the technology rises over time, and dispositional trust can be influenced by cultural, age, gender, and personality qualities. [14, 21].

System acceptance is a more comprehensive concept that incorporates trust as one of its contributing elements, although trust may not always translate to system acceptance, even while it represents a user's belief in the system's capacity to operate as intended.[34]. According to the Technology Acceptance Model (TAM), system acceptance is driven mainly by perceived usefulness and perceived ease of use [6]. These factors eventually influence the user's attitude and behavioral intention toward using the system. The TAM model was extended further into TAM2 by modeling the social and cognitive factors that influence perceived usefulness [35], yet it did not fully model how perceived ease of use develops over time. Later, TAM3 was proposed, incorporating determinants that affect the perceived ease of use [34].

Although models like TAM focus primarily on usability and usefulness, recent research highlights that calibrated trust is a crucial factor for the safe and sustained adoption of AVs [33].

2.2 Trust Calibration via Transparency

Numerous studies have been carried out to investigate the elements that affect a human operator's confidence in automation [11, 14]. System transparency has emerged as one factor to maintain appropriate trust calibration [7, 23]. According to a number of experimental studies, giving the driver/user information typically improves driving performance and acceptance in fully [22] and partially [13, 19, 36] automated driving systems. For example, Verberne et al. [36] discovered that Adaptive Cruise Control (ACC) systems that support drivers' goals, such as adopting a safe and relaxed driving style free of abrupt braking and accelerations, while also keeping the user informed, are regarded as more dependable and acceptable. Koo [19] examined the effects of providing "how" and "why" information in the context of an auto braking system. Providing both forms of information led to the safest driving practices but at the expense of low acceptability and a high cognitive burden. Drivers often believed that "how" information was redundant and preferred to only be provided "why" information. The interfaces developed in these studies were relatively simple compared to the technical capabilities of modern user interfaces: they either only offered information about the location of obstacles [22] or consisted of short spoken statements without any visual cues [19]. There are multiple options to inform the user of his vehicle's intentions through different sets of displays. These displays are commonly categorized into three basic types: head-down displays (HDDs), head-up displays (HUDs), and head-mounted displays (HMDs). It has been shown through research that Augmented Reality HUDs (AR-HUDs) are best suited to assist drivers' situational awareness [28], especially in demanding driving conditions [10].

2.3 The Emerging Role of Augmented Reality

Recent studies highlight the potential of AR interfaces to improve situational awareness, user acceptance, and trust in autonomous vehicles. According to experiments, AR windshields that implicitly communicate "how" and "why" information significantly increase situation awareness and trust, especially in situations when safety is crucial [24]. Similarly, adding semantic segmentation [5] and uncertainty in the planned path [4] integrated with AR displays, allowed users to understand the AV's perception and planning with little mental strain. Augmented reality (AR) has also been demonstrated to improve acceptability in FAVs by improving passenger visibility in unclear weather [38]. Additionally, AR visualizations for parking conditions increase user experience and perceived system transparency [25]. While these interfaces have been shown to enhance trust and transparency between passenger and ego vehicles, the future of AVs will include multi-agent and cooperative systems relying on V2X technologies to communicate their intentions. The human autonomy teaming (HAT) framework emphasizes having a shared mental model (SSMs), which can be understood as a knowledge structure that is shared across members of a team, enabling them to form better explanations and expectations for their tasks [17]. If one agent is perceived as failing or untrustworthy, this may result in an erosion of trust; this claim is supported by [37]. In these situations, effective trust calibration will require a broader transparency extended to other agents within an environment in order to highlight coordination behavior across agents and ensure a mutual understanding and shared intent across the multiple actors.

3 Research Questions and Hypotheses

While previous research [4, 5, 24, 25, 38] has shown that system transparency can enhance trust and situational awareness, much less is known about how passengers form trust with other cooperative road users, or how different interface designs might affect users' trust in multi-agent environments.

To investigate this, we designed three interface concepts that varied in their transparency toward the environment, from minimalist (Concept A), to system-transparent (Concept B), and environment-transparent (Concept C) approaches. We then posed the following research questions:

- **RQ1:** How do different transparency concepts - minimal transparency, system-level transparency, and environment-level transparency -affect passenger trust in the ego vehicle and surrounding cooperative AVs during cooperative maneuvers?
- **RQ2:** How do these transparency concepts influence situational awareness and perceived cognitive workload in cooperative driving scenarios?
- **RQ3:** How do different transparency concepts impact user acceptance of cooperative autonomous vehicles?

Based on these questions, we derived the following hypotheses:

- **H1:** Environment-level transparency enabled by V2X (Concept C) will lead to higher trust toward ego vehicle and other autonomous vehicles.
- **H2:** Environmental-level transparency will lead to higher situational awareness.
- **H3:** Higher transparency levels (Concept C) will be associated with increased cognitive workload.
- **H4:** Despite increased cognitive demand, environment-level transparency will result in higher user acceptance due to improved perceived safety and understanding.

4 Methodology

4.1 Interface Design

The baseline interface shared only the vehicle's speed (Concept A). Interface B represented Concept B, which included a visualization of the ego vehicle's planned path. Interface C corresponded to Concept C and extended the display to show V2V and V2I communication data, including the planned paths of surrounding vehicles, road conditions such as road blockage, and indicators to notify the passenger in the case of cooperative maneuvers. We developed a custom path planning algorithm to relay road condition information and cooperative maneuvers through a customized DReyeVR pipeline to the passenger. The three interfaces are shown in Figure 2. The AR interfaces were designed to investigate not only how passengers interpret their own vehicle's behavior, but also how they build trust in cooperative multi-agent systems.

4.2 Scenario Design

The scenario included cooperative maneuvers and abrupt stops to test participants' ability to interpret vehicle intentions and cooperative behavior. The scenario starts with the ego vehicle traveling within the urban environment at 30 km/h, which is relatively faster than the surrounding traffic. As the vehicle approaches the entrance of the tunnel, a road blockage suddenly appears. A firetruck ahead of the ego vehicle abruptly swerves to the left, triggering the need for a quick maneuver to the left. Interface B allows participants to predict the ego vehicle's intentions through the visualized planned path, while interface C allows participants to predict the behavior of the firetruck and their own vehicle, as the whole environment information can be seen through a mini-map with indicators indicating a road blockage ahead of nearby vehicles. As the vehicles are moving through the tunnel, a cooperative maneuver occurs, and the firetruck moves to the right after receiving a lane change request from the ego vehicle. Interface C shows this to participants through indicators of communication between their vehicle and the firetruck, while Interface B only shows the intended path of participants' own vehicle through the maneuver. The scenario continues with multiple vehicles suddenly cutting the path of the ego vehicle. Interface C makes participants aware in advance by means of visual indicators and a mini-map. The scene concludes with the ego vehicle taking a sharp right before entering a roundabout, followed by sudden road obstruction which requires a right swerve before arriving at a gas station. The full scenario is shown in Figure 3. It was designed to test the participants' understanding of the vehicle's cooperative maneuvers and challenge their expectations towards the behavior of their vehicle and other vehicles.

4.3 Participants

We recruited 30 participants (18 male, 12 females; ages ranging from 18 to 34, M = 23.8 SD = 4.05), mostly Egyptian graduate and undergraduate students. Participation was voluntary, and participants did not receive any compensation for their participation in the experiment. The study conducted was approved by the Institutional Review Board (IRB) at the researchers' institution, and a signed informed consent form was collected from each participant.

4.4 Experimental Setup

The experiment was carried out within a controlled environment to minimize any possible distractions throughout the experiment and ensure a consistent environment for all participants. This apparatus included the following components:

(1) HTC Vive Pro Eye was utilized for the experiment as it has a combined resolution of 2880 x 1600 pixels. Those headsets provide graphics with rich colors, and headsets also support headphones integrated with 3D spatial sound for immersive audio.
(2) A workstation was used to run the simulation smoothly at 30 FPS, ensuring minimal delay between viewpoint updates and reducing the risk of motion sickness.
(3) Participants were seated in a fixed chair, and the steering wheel was eliminated from the simulator and from the physical setup since the experiment ran within the context of level 5 autonomy.
(4) For the sound, the experiment used the default sound provided by the DReyeVR simulator to immerse the participants within the scenario.

4.5 Procedure

The study employed a within-subjects approach to measure the levels of trust and acceptance experienced by the participants in cooperative fully autonomous vehicles. Each participant was given a brief introduction to the experiment before participating, which included its purpose, setup, and procedural sequence. The different indicators of each interface design were explained, ensuring a correct understanding of the interface before the experiment. Participants received a brief instructional introduction to fully autonomous vehicles as well. A calibration process for participants was carried out to ensure all participants experienced the vehicle from the same point of view, regardless of their height. Subjects were notified of potential risks associated with virtual reality equipment or the experiment, including cognitive overload and motion sickness; none of the participants reported any sickness before or after the process. All participants submitted informed consent before the start of the experiment. Each scenario was given a time of three minutes. During the scenario, the participants were asked to monitor the behavior of their vehicle and the cooperating agents. After finishing each scenario, the participants responded to the concept questionnaire to capture participants' trust, situational awareness, cognitive load, and acceptance. Each participant experienced three different interfaces. The entire procedure took 40-50 minutes to complete; at the end of each concept questionnaire, participants were also asked to describe their experience with each interface in an effort to gather additional qualitative data. Figure 4 describes the experimental procedure and its order.

4.6 Dependent Variables and Data Analysis

To measure trust in automation, we utilized Jian et al. [16]'s work because it provides a multifaceted, validated framework for assessing automated systems' trustworthiness. A 7-point Likert scale is used to quantify each dimension, enabling us to capture participants' detailed responses. To better fit our experiment and to reduce the experiment duration, a subset of seven of the original questions was selected, excluding questions that were not relevant or that represented constructs that were already addressed through other questions. To measure situational awareness, SART by Selcon et al. [31] was used because it can capture important aspects of cognitive effort, comprehension, and attentional concentration, all of which are relevant to the setting of our autonomous driving experiment. For cognition load, we used the NASA Task Load Index[12] for its wide acceptance and reliability in assessing the perceived cognitive workload across multiple dimensions. Finally, the Technology Acceptance Model (TAM) [6] was used to measure acceptance toward the AVs.

Participants' survey results were analyzed using the Wilcoxon signed-rank test. This was selected for its suitability for non-parametric

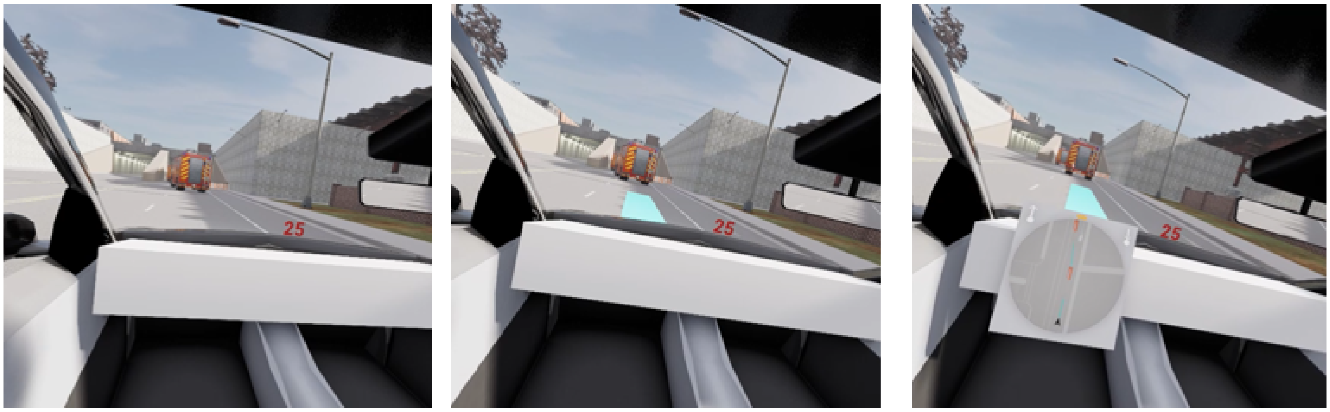

Figure 2: Overview of the interface concepts used in the study (from left to right). (A) No Transparency: only shows vehicle speed. (B) System-Level Transparency: displays ego vehicle's planned path. (C) Environment-Level Transparency: visualizes cooperation intentions, other vehicles planned path and infrastructure information using V2X.

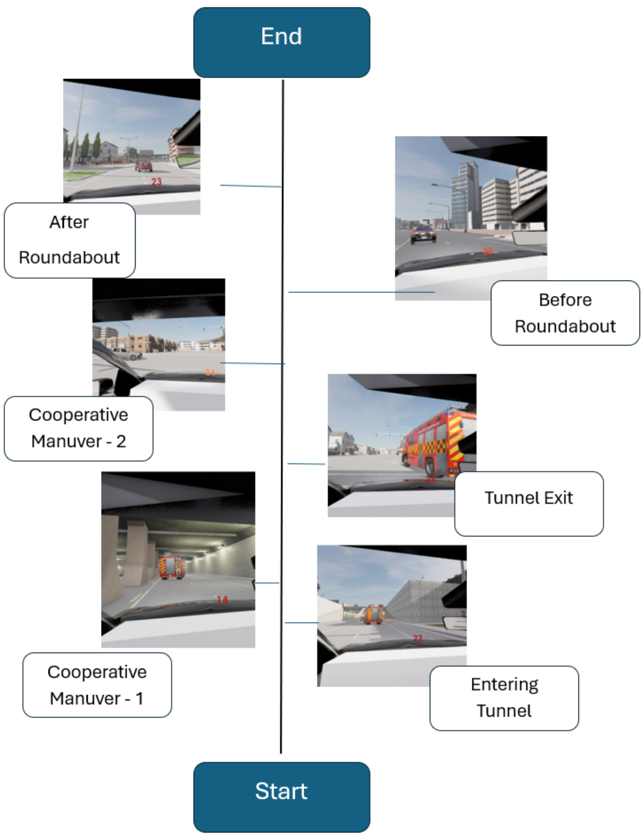

Figure 3: Driving scenario overview.

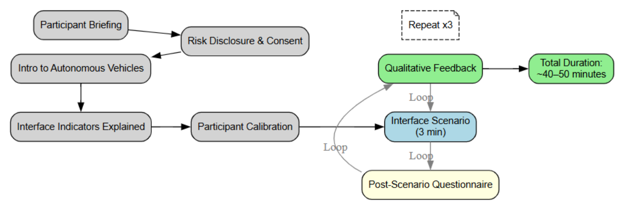

Figure 4: Experiment Procedure

(tested through the Shapiro-Wilk test), within-subjects data. An alpha value of 0.05 was used, and all p-values were adjusted using the Bonferroni correction to account for multiple comparisons on the same data.

5 Results

5.1 Quantitative Results

5.1.1 Trust Toward the Ego Vehicle. Analysis of the data showed that the interfaces' transparency levels had a significant impact on users' trust towards the ego vehicle.

Participants reported higher trust values for Interface C (Environment-Level Transparency Display, $M = 5.442$, $SD = 1.140$) compared to Interface A (No Transparency, $M = 2.101$, $SD = 0.931$), with ($W = 5.0$, $p < .001$), and a large effect size ($r = 0.854$). For Interface C against Interface B (System-Level Transparency, $M = 4.175$, $SD = 1.117$), the comparison yielded ($W = 53.5$, $p < .001$), and ($r = 0.672$), indicating a significantly higher level of trust in the ego vehicle. Additionally, trust ratings in Interface B also significantly exceeded those in Interface A, with ($W = 3.5$, $p < .001$), and ($r = 0.860$). These results are shown in Figure 5.

5.1.2 Trust Toward Other Cooperative Vehicles. Participants' trust toward other AVs was also significantly higher for Interface C (Environment-Level Transparency Display, $M = 4.876, SD = 1.306$) compared to Interface A (No Transparency Display, $M = 2.069, SD = 1.062$) ($W = 16.0, p < .001$) with a large effect size ($r = .813$). When comparing Interface C against Interface B (System-Level Transparency, $M = 2.982, SD = 1.203$), trust ratings were significantly higher in Interface C ($W = 13.0, p < .001, r = .824$). Trust toward

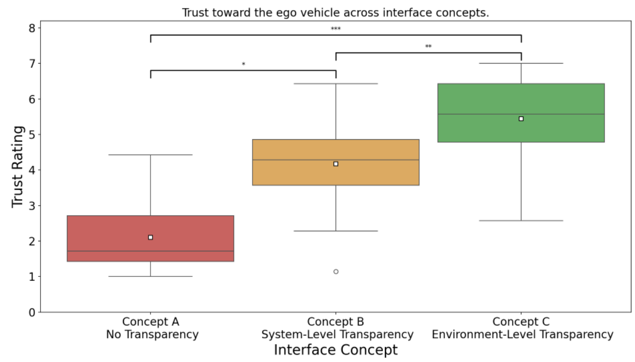

Figure 5: Perceived trust in the ego vehicle across interfaces. Trust ratings were significantly higher in Interface C compared to A and B.

other vehicles was also higher in Interface B compared to Interface A ($W = 29.0, p < .001, r = 0.764$). These results are shown in Figure 6.

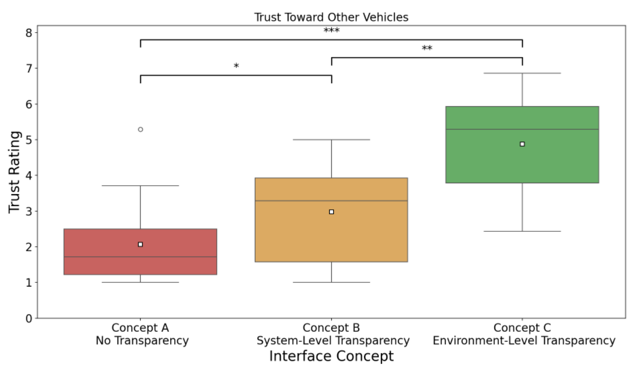

Figure 6: Perceived trust in cooperative vehicles across interfaces. Participants reported significantly higher trust in Interface C (Environment-Level Transparency) compared to Interfaces A and B. Significance levels are indicated above.

5.1.3 Cognitive Workload. The least amount of cognitive workload resulted from Concept B (System-level transparency; $M = 2.349$, Median = 2.167, $SD = 0.943$). The most demanding interface was Concept C (Environment-level transparency; $M = 2.952$, Median = 2.833 $SD = 1.336$), followed by Concept A (no transparency; $M = 2.548$, Median = 2.167, $SD = 0.738$).

Nevertheless, no significant differences were found between Concept C vs. A ($W = 162.0$, $p = 0.4407$, $r = 0.303$), Concept C vs. B ($W = 139.0$, $p = 0.1629$, $r = 0.384$), and Concept B vs. A ($W = 126.0$, $p = 0.1428$, $r = 0.429$) according to Wilcoxon signed-rank tests. These results are depicted in Figure 7.

5.1.4 Situational Awareness. Regarding situational awareness, participants reported the highest level of situational awareness for Interface C ($M = 5.600, SD = 1.003$), followed by Interface B

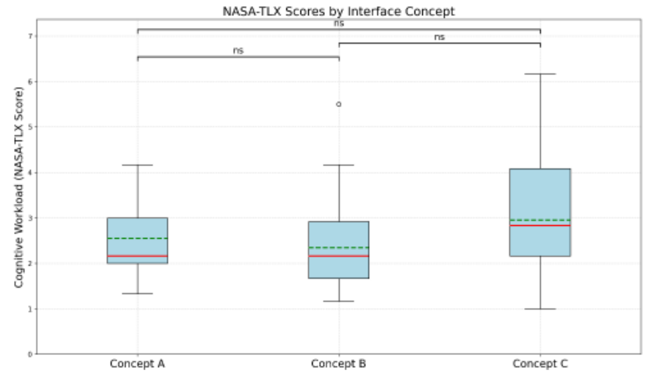

Figure 7: Perceived cognitive workload (NASA-TLX) across interfaces. Workload was insignificantly higher in Interface C compared to both Interface A and Interface B.

($M = 4.211, SD = 1.070$) and Interface A ($M = 1.822, SD = 0.892$) resulted in the least situational awareness. Interface C showed a significant difference against Interface A ($W = 0.0, p < .001, r = 0.873$) and Interface B ($W = 32.5, p < .001, r = 0.751$), while situational awareness resulting from Interface B was also significant when compared to A ($W = 2.5, p < .001, r = 0.864$). These results are shown in Figure 8.

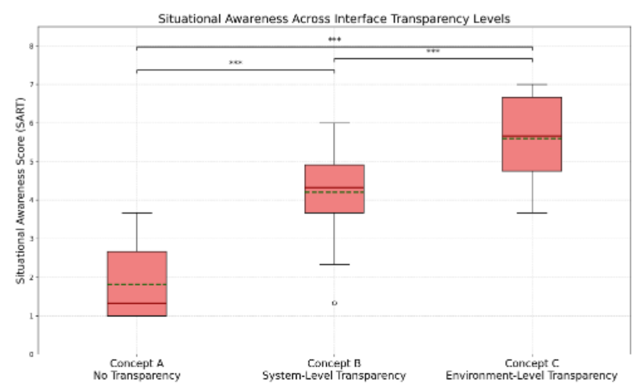

Figure 8: Perceived situational awareness across interfaces. Interface C led to significantly higher situational awareness ratings compared to both Interface A and Interface B.

5.1.5 Technology Acceptance Model. For TAM, several aspects were measured: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Attitude Toward Use (ATT), Trust, and Behavioral Intention (BI).

For Perceived Usefulness (PU), Interface C significantly outperformed both B and A, and B significantly outperformed A ($p < .001$ in all cases), with a large effect size ($r = 0.753$–0.873). This shows a strong perceived benefit in functionality toward vehicles with Interface C compared to those with Interface A and B. For Perceived Ease of Use (PEOU), the vehicle was rated as significantly easier to use when participants were shown Interface B over Interface

A ($p = .0403, r = 0.576$). However, there were no significant differences between perceived ease of use for the ego vehicle when Interface B versus C were shown, or even when A versus C were shown.

For Attitude Toward Use (ATT), users expressed significantly more positive attitude toward Interfaces B and C compared to A ($p < .001, r \geq 0.839$). When comparing B and C, no significant difference was observed, indicating similar emotions toward the two interfaces. In terms of trust, Interface C received the highest trust ratings, significantly surpassing both A and B ($p \leq .0038, r = 0.691–0.873$), while Interface B also significantly outperformed Interface A ($p < .001$, $r = 0.854$).

Finally, Behavioral Intention (BI), which is a key indicator of acceptance, was significantly higher for Interface C compared to both Interfaces B and A ($p < .001$) and for Interface B compared to Interface A ($p = .0001$), with large effect sizes in all comparisons ($r = 0.601–0.873$). These results support the hypothesis that Interface C was the most accepted design overall. These results are shown in Figure 9.

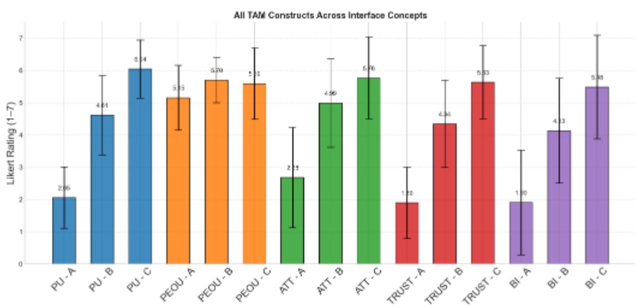

Figure 9: Perceived TAM construct ratings across interfaces. Interface C consistently received higher ratings across all constructs, including perceived usefulness (PU), attitude (ATT), trust, and behavioral intention (BI), indicating stronger acceptance and preference compared to Interfaces A and B.

5.2 Qualitative Results

Participants were able to share their experience with each interface concept qualitatively in the questionnaire. Their responses showed how different interface designs can affect their trust and perceived cognitive load.

5.2.1 Interface A. Users' feedback was mainly negative toward Interface A. The most prominent theme was the unpredictability and uncertainty the interface created toward the ego vehicle. Participant P15 reported, "I was not able to predict where my car is going...the car was moving and stopping at random times." Another participant, P25, described the experience as "Very disorienting; I had no idea what to expect. I hate surprises, so this was horrible." When viewing Interface A, participants described the experience as "stressful," "scary," and "mentally exhausting." For example, P22 expressed, "It was quite unpleasant to be in this car. I'm naturally an anxious driver. . . the car's sudden, inexplicable responses...left me with a heightened sense of fear and mental effort." Another participant expressed frustration with the lack of situational awareness. P21 described his experience: "In Interface A, I faced one major problem: abrupt stops without any information about other vehicles. I had no idea if vehicles around me would stop or turn, so it gave me a high degree of threat and doubt about possible accidents."

5.2.2 Interface B. For Interface B, which provided system-level transparency through visualization of the ego vehicle's planned path, participants' feedback was generally more positive compared to Interface A. However, they still had some concerns regarding trust in other vehicles.

On one hand, users reported being able to anticipate the ego vehicle's behavior. P11 noted, "I can now at least tell the general direction of the vehicle and when it is going to brake. . . it is overall better than interface A." P21 expressed, "it has an advantage that gives me full information about the pathway of my vehicle but it doesn't give an overview about the other vehicles around me therefore i have trust issue about the safety of my vehicle."

On the other hand, while many felt confident in their vehicle's behavior, they expressed discomfort with other vehicles' intentions. For example, P27 wrote, "It did not give the same sense of safety as interface C did, but it was still safe to some extent, not knowing that there were other cars near me, and suddenly finding them was not nice at all. "

5.2.3 Interface C. For Interface C, which incorporated environment-level transparency utilizing V2X information, users' sense of awareness was enhanced. Many participants reported a reduced level of uncertainty and expressed other vehicles were less threatening and more understandable. One described this by stating, P21: "...It gives me the full information about the vehicle pathway and the interactions between other vehicles when they will stop and when they will make decisions to turn right or left." Other participants reported that being able to see what other vehicles are willing to do helped them feel prepared for other vehicles' maneuvers. As P30 noted, "The map helps me understand how the vehicles interact with each other," and P1 said, "The screen enabled me to predict the behavior of the vehicle and its surroundings."

A number of participants also expressed concerns regarding workload, the amount of information presented to passenger was described to be overwhelming multiple times. for example P5 reported "Overwhelming amount of information although it greatly helped me build trust with the vehicle.", P13 noted, "..the amount of information communicated is a bit much.."

In summary, qualitative responses supported qualitative results and showed that Interface C benefited from enhanced levels of trust toward ego vehicles and other autonomous vehicles using the road and higher levels of situational awareness than Interfaces A and B, but at the cost of a higher cognition load.

6 Discussion

The findings of this user study demonstrate how passengers' trust, situational awareness, and acceptance of cooperative autonomous vehicles are influenced by interface transparency. Our hypothesis was supported by the fact that environment-level transparency made possible by V2X technology significantly improved trust in both nearby autonomous vehicles and ego vehicles. This result is consistent with earlier research that shown the influence of "how" and "why" explainability on automated system trust and system transparency[7, 19, 24]. The results also provide strong evidence that signaling the user regarding cooperative intentions and infrastructure information can bridge the trust gap in cooperative scenarios. Interface C allowed participants to develop an environmental understanding, which translated into increased trust and predictability regarding the different cooperative vehicles.

Interface B (system-level transparency) improved trust relative to the baseline (Interface A), but failed to deliver the same level of confidence toward surrounding cooperative vehicles as compared to Interface C. Participants showed higher situational awareness using Concept C, and this shows the potential of V2X information to enhance users' understanding of different vehicle's intentions and the surrounding environment. However, this increase in awareness came at the cost of an insignificant increase in cognitive workload, which can be explained from the subcomponents of the task load index. Interface C resulted in higher significant mental, physical, and temporal loads, but the interface also enhanced the user's performance in monitoring the vehicle, resulting in an overall insignificant combination. This can also be observed from the qualitative feedback. Yet this increase in mental demand aligns with existing literature that reported an insignificant increase in cognitive load with augmented reality interface [5].

Despite the higher workload, Interface C was the most accepted among participants based on TAM measures; the perceived usefulness and behavioral intention scores strongly favored environment-level transparency, indicating users will likely adopt a system that provides environment-level transparency. While interface C increased the cognitive workload slightly among participants, they did not consider the ego vehicle itself as significantly harder to use when Interface C was compared to Interfaces A or B. This is likely because even though Interface C was more complex, they perceived it as more informative in terms of understanding the vehicles' behavior, which made them perceive the ego vehicle itself as easier to use. These findings show that the potential of V2X information can be essential to improve user trust and awareness in connected FAVs.

7 Limitations and Future Work

Our study shows the benefits of environment-level transparency or providing users with information beyond the ego vehicle in enhancing trust toward other cooperative agents. However, some limitations remain. Firstly, the small sample size of participants and their demographic homogeneity might impact the generalisability of the results produced.

Secondly, the optimal range within which V2X information should be provided to positively impact trust remains unclear. For example, whether users' trust toward other autonomous vehicles or the ego vehicle is affected by knowing the behavior of other vehicles that are 10 kilometers away versus 10 meters away, or if there is even a certain range where this trust saturates. Future work should therefore consider exploring these aspects.

Thirdly, we did not collect data on participants' prior driving experience or familiarity with autonomous systems. These factors could have influenced baseline trust, workload perception, or situational awareness.

Fourthly, although users showed increased trust in surrounding vehicles, but we did not measure their trust in the coordination between vehicles itself. Trusting other individual agents does not imply a trust in the coordination between them. This is also an interesting distinction for future work to explore. This distinction is also especially true in the case of more cooperative and complex maneuvers, such as platooning or cooperative lane merging.

Fifthly, Interface C increased both trust and cognitive load. It is possible that an adaptive or context-aware interface could optimize between both, and should also be tested.

Finally, for reasons pertaining to safety, replicability, and practicality, and in line with previous work, this study was carried out in a VR environment. It is possible that viewing the AR interfaces in a real-world setting might yield different results.

Future studies might investigate mixed traffic, including lower autonomy level vehicles alongside fully autonomous vehicles, to explore how the interface influences trust toward other cooperative agents and how to address overtrust within such an environment, or investigate more complex cooperative maneuvers, such as platooning.

8 Conclusion

This study has demonstrated how different interface transparency levels can affect users' acceptance, cognitive load, situational awareness, and trust in a cooperative autonomous vehicle. Three interfaces that provided minimalist, system-level, and environment-level information were tested in a within-subject experiment utilizing virtual reality. Our findings demonstrate that user trust in the ego vehicle and other cooperative road users is significantly impacted by environment-level feedback made possible by V2X technology. On measures of acceptability, situational awareness, and trust, Interface C, which displayed both system and environment information, performed noticeably better than the other two interfaces. Users reported feeling more informed and better prepared for the road conditions and vehicle behavior. However, this came at the expense of an insignificant increase in cognitive workload, while still maintaining comparable levels of perceived ease of use. The results indicate that the combination of V2X information and an augmented reality interface can be an important element for establishing trust in cooperative autonomous vehicles.

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