Drive Right: Shaping Public's Trust, Understanding, and Preference Towards Autonomous Vehicles Using a Virtual Reality Driving Simulator

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Abstract

While autonomous vehicles are being increasingly introduced into our lives, people's misunderstanding and mistrust have become the key factors hindering the acceptance of these technologies. In response to this problem, proper work must be done to increase public's understanding and awareness of self-driving and help them rationally evaluate the system. The method proposed in this paper is a virtual reality driving simulator which serves as a low-cost and reliable platform for autonomous vehicle demonstration and education. To test its validity, we recruited 36 participants and conducted a test drive using three different scenarios. The results have shown that our simulator successfully increased participants' understanding and awareness of the autonomous system and changed their attitude to be more positive. The methodology and findings presented in this paper can be further explored by policy makers, driving schools, and auto manufacturers to improve the legislative and technical process in the field of autonomous driving.

Keywords
Autonomous Vehicle, Virtual Reality, Education.

1. Introduction

1.1. Background & Motivation

Autonomous vehicles (AVs) have been gaining unprecedented attention and popularity as the society eagerly expects a revolution in the transportation industry. However, the concept of autonomous driving (AD) still sounds mysterious and even scary to many people. Research has shown that the public has a natural tendency to resist AVs and often require them to be significantly safer than human-driven vehicles (Liu, Wang, & Vincent, 2020). Similarly, AV related malfunctions and accidents tend to be overly dramatized in the media which further jeopardizes public trust (Liu, Du, & Xu, 2019).

As we are still experiencing the stage of rapid development of AVs, it is unlikely that in the near future, AVs will completely eliminate traffic accidents and outperform humans in every aspect. Nevertheless, they have the potential to: significantly reduce traffic accidents, increase traffic efficiency, consume less energy, and provide an alternative way of transportation (Hasan, & Hentenryck, 2021). In order for society to fully accept AVs and enjoy their benefits, work must be done to increase the public's understanding of these innovative technologies (Abraham, Lee, Brady, Fitzgerald, Mehler, Reimer et al., 2017). The best way to do this is for someone to ride in an AV with a safety expert behind the wheel. However, such demonstrations can be costly and time-consuming. Moreover, the test drive is subject to traffic, weather, and geographical conditions and may not provide the most comprehensive evaluation (Kalra, & Paddock, 2016).

As a solution to these problems, a driving simulator stands up as a cost-effective, time-efficient, and completely safe platform to demonstrate the capabilities of AVs. Driving simulators support the testing of different scenarios that might be dangerous or risky to attempt in the real world (Malik, Khan, & El-Sayed, 2022). They are also accessible to people from all backgrounds and with varying driving skills. This work is a continuation of our previous drive right effort which aimed at increasing public's understanding and trust towards AVs using a simulation educational platform (Qiao, Loeb, Gurrla, Lebermann, Betz, & Mangharam, 2022). Our previous study has shown that the simulator education could effectively decrease participants' perceived risk and increase the perceived usefulness towards AVs. In this study, we developed a virtual reality (VR) driving simulator based on the open-source Carla (Dosovitskiy, Ros, Codevilla, Lopez & Koltun, 2017). Our simulator allows the user to sit in the driver's seat and control the vehicle like real. The software system is coupled with a Logitech G29 steering wheel & pedal set to further increase the simulation fidelity.

1.2. Target Population

The target population of this work are drivers who have had experience with conventional vehicles but lack the knowledge of AVs. According to the SAE 5 levels of automation, driver's input is required by varying amounts except at level 5 (SAE International, 2021). In the near future, we will likely see level 2 and level 3 automation for privately owned vehicles, and level 4 for shared taxis and shuttles. Although the vehicles are not fully automated at this stage, there is no doubt that with each increased level of automation, driver's pressure and workload will be tremendously decreased. However, it is essential that the drivers understand the capabilities and limitations of the AV at each level, instead of blindly trusting it or not trusting it at all (Kaye, Somoray, Rodwell, & Lewis, 2021).

Therefore, we designed a level 4 AD in our simulator that is robust and reliable in most circumstances. The AD was developed based on the Carla built-in modules but modified to support more intelligent and adaptive behaviors. We hope that this will help drivers understand what it feels like to ride in an AV, how they should interact with it, and if an AV is a good fit to them. Note that our AD was set at level 4 mainly to fulfil the goal of AV education and trust development. In other circumstances, the AD can be adjusted to level 2 or level 3 to match the capability of a target vehicle. Through this implementation, we wish to show the application of a driving simulator and its potential in the AV field.

1.3. Research Questions

For the considerations outlined above, this work examined two research questions. The first question is about improving users' attitude towards AVs, and the second is on the applications of a driving simulator. The main method for evaluation is human study and survey collection.

- H1a: A driving simulator decreases the user's perceived risk towards AVs.
- H1b: A driving simulator increases the user's perceived usefulness towards AVs.
- H1c: A driving simulator increases user's perceived ease-of-use towards AVs.
- H1d: A driving simulator increases user's trust towards AVs.
- H1e: A driving simulator increases the user's behavioral intentions towards AVs.

- H2a: A driving simulator is good at auto dealerships for AV demonstration.
- H2b: A driving simulator is good at driving schools for AV education.

1.4. Contribution

This work contributes to existing literature in the following ways:

1. It is the first systematic approach to deploy the Carla driving simulator into the VR framework while extending its driving algorithm validation purpose with the human factor consideration. Our development provides an easy-to-follow approach and allows the use of Carla on any VR headset. Full instructions are available on our lab website under the MIT open license (xLab, 2022).

2. It is the first attempt to take the AD system as a whole and focus entirely on user experience and interaction. In our simulator, everything is designed from a user standpoint to help them form an understanding of the AVs in a vivid and immersive environment.

3. We present the rationale of using a driving simulator and show why it can be such an effective tool for AV education and demonstration. The results from our study should provide some guidance for the auto dealerships, driving schools, and policy makers to promote safe AV education and demonstration.

2. Literature Review

2.1. Overview

Extensive efforts have been made by academia and industry to increase people's understanding and trust towards AVs. A large portion of these attempts involved some real or simulated AV riding experience, with different design and focus. In a general sense, the authors summarized existing literature on AV trust into four groups: information delivery, takeover measurement, risk analysis, and riding experience.

2.2. Information delivery

Research has been done to explore what kind of information should be displayed by an AV, and in what form it should be displayed. One popular choice is anthropomorphism, which is to design the vehicle interface to mimic human tones and facial expressions, hoping to reduce human mistrust by depicting the machines as more "human" (Waytz, Heafner, & Epley, 2014; Lee, & Lee, 2022; Niu, Terken, & Eggen, 2018; Ruijten, Terken, & Chandramouli, 2018). Another technique, which has been adopted by many designers, is to display a complete set of information of the vehicle's surroundings (vehicles, traffic signs, pedestrians) as well as its planned movement. This technological transparency will portray the AV as both intelligent and capable (Ma, Morris, Herriotts, & Birrell, 2021; Morra, Lamberti, Pratticó, Rosa, & Montuschi, 2019).

2.3. Takeover Improvement

In a simulated takeover experiment, the AV is perceived as Level 2 with advanced driver's assistance or Level 3 with conditional automation. Either way, the researchers deliberately add system failures and try to measure the participant's takeover response. In (Ebnali, Hulma, Ebnali-Heidari, & Mazloumi, 2019), the difference was measured between no training, video training, and the monitor simulator training group, while in (Ebnali, Lamb, Fathi, & Hulme, 2021), it was the video, low-fidelity VR, and high-fidelity VR training group. Researchers found out that training has a positive impact on the takeover response while the more immersive tools tend to achieve better results.

2.4. Risk Analysis

Researchers have been trying to understand the root of people's mistrust towards AVs, and much work can be summarized as an investigation of the "internal" and "external" risk. The internal risk is associated with the AD system's perceived reliability, while the external risk is related to environmental conditions (Azevedo-Sa, Zhao, Esterwood, Yang, Tilbury, & Robert, 2021). Studies have shown that external risk, regardless of traffic or weather, is not a major factor (Ha, Kim, Seo, & Lee, 2020). Rather, the internal risk, which is linked to people's fear and bias, affects the evaluation of the technology. In multiple experiments, researchers found that the participants consistently degraded the performance of AVs when compared to human-driven vehicles even though the driving style was exactly the same (Mühl, Strauch, Grabmaier, Reithinger, Huckauf, & Baumann, 2020).

2.5. Riding Experience

The most effective way to change people's attitude towards AVs is to let them ride in one in traffic. However, due to safety concerns and legal restrictions, such an attempt is not always feasible. One solution is to provide AV riding in a closed testing field at a relatively low speed. For instance, Paddeu et al measured comfort and trust on a shared autonomous shuttle (Paddeu, Parkhurst, & Shergold, 2020), while (Liu, & Xu, 2020) demonstrated the capabilities of an AV to change the ambivalent group to be more positive.

Another option is to let a human driver control the vehicle, but create the illusion of AD. In (Baltodano, Sibi, Martelaro, Gowda, & Ju, 2015), the driver was physically hidden from the passenger, and in (Zou, O'Hern, Ens, Coxon, Mater, & Chow et al, 2021) the passenger wore a VR headset, which received the vehicle movement information and got the corresponding update in the digital twin.

3. Design

3.1. Carla

Carla is an open-source driving simulator introduced for AD algorithm development and validation research. Its rigorous environmental assets, complete sensor suite, and full control over all actors, make it a suitable platform to conduct AV-related experiments. The research team chose to use Carla to take advantage of its well-designed mainframe so that significant work can be saved from developing a new simulator and more focus can be put on designing the study and exploring the research questions.

3.2. Carla VR

While the standalone Carla package is built in the 3D environment, it does not come with the VR capability. As a result, the research team had to add the OpenXR plugin and rebuild the project to enable rendering on an Oculus Quest 2 headset. To achieve this, the Carla project source code and a Carla-customized fork of UE4 were downloaded from the official platform. Then, the UE4 was built using the Visual Studio 2019, Windows 8.1 SDK, x64 Visual C++ Toolset, .NET framework 4.6.2, and the Carla server & client was compiled using the x64 Native Command Tool. To set the OpenXR, the plugin was first enabled inside the Carla UE4 project, and then activated through the Oculus Link in the Meta Oculus application. Finally, the OpenXR runtime for Oculus was installed and added to the environmental variables. In this way, if the project requires another headset in the future, it can be easily implemented by replacing the path and re-compiling the project.

3.3. Vehicle Mesh Rendering

Since Carla is designed primarily for AD algorithm research validation, it shows vehicles in the third-person view, and all vehicles have a mesh and texture with a low Level of Detail (LOD). To use Carla in the VR application in the first-person view, a high LOD vehicle with interior modeling must be imported from the outside source. After searching and comparing a variety of models, we selected an Audi A6 model from the Car Configurator Project and cleared irrelevant nodes (see Fig. 1, Fig. 2). This model was developed by Epic Games and supports a free license when working with the Unreal Engine. In addition, a Blueprint class called *AutoAttachedCamera* was developed, which actively looks for a player-controlled vehicle and then automatically disables its LOD mesh rendering and replaces that with the high LOD Audi A6 rendering. If a previous player vehicle is destroyed and a new one has been generated, the camera will automatically move to the new vehicle. In this way, the spawning event is properly handled between the server and the client.

Fig. 1. Audi Vehicle Model Exterior View.

Fig. 2. Audi Vehicle Model Interior View.

3.4. Logitech G29

Logitech G29 is a racing force steering wheel & pedal set that is suitable for various driving tasks. In our simulator, G29 plays two different roles: manual and autonomous. In the manual mode, the user uses the steering wheel to control the direction of the vehicle, and the throttle and brake pedals to adjust the speed. The vehicle is assumed to have automatic gear so shift that no input from the clutch or the shifter is required. Systematic tests have shown that the processing time from the user input to the simulator response takes less than 100 microseconds, and therefore can be safely neglected.

Fig. 3. Left: functions for buttons and switches. Right: physical and simulation wheel correspondence.

The autonomous mode can be triggered by pulling the switch on the left side of the steering wheel. To exit, the user can use the switch again or lightly press the brake pedal. The switch on the right side of the steering wheel is used to toggle the reverse mode. Note that in both the manual and autonomous mode, the physical steering wheel perfectly mimics the position of the virtual wheel in the simulated car model (see Fig. 3). This helps reduce any sensing discrepancy between the physical wheel and the simulation while minimizing the discontinuity during a driving mode switch.

3.5. Wheel Match

The wheel position match was easy to implement in the manual mode, as the engine could simply read the physical wheel position and reflect that on the simulator. In the autonomous mode, however, it was the physical wheel trying to match the commanded simulated wheel position. This was achieved by controlling the G29 wheel's internal motor force and friction using NodeJS (Nightmode, 2021). In addition, a PID controller was implemented which took in the difference between the commanded angle and the actual angle and output the desired force and friction. Fig. 4 drawn from an extended data collection period shows that the physical wheel could match the position of the simulated wheel with negligible delay and error.

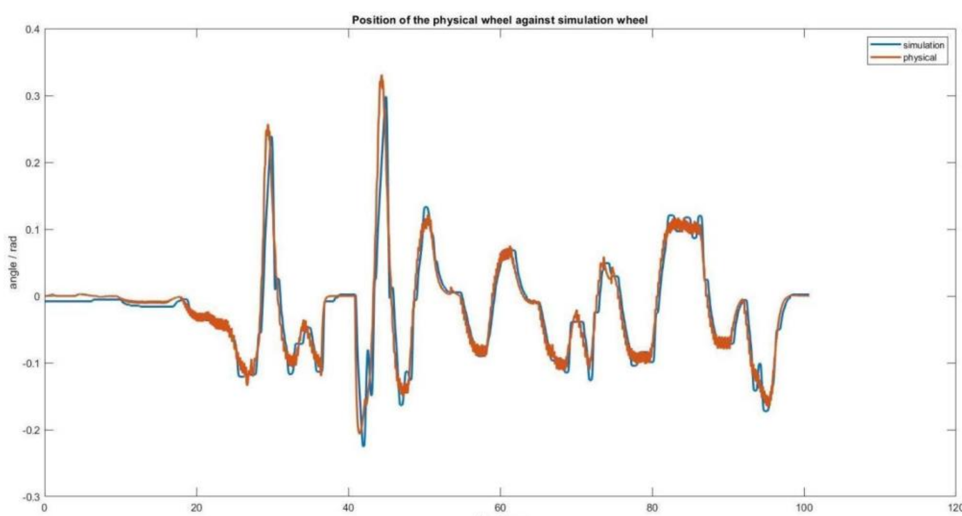

Fig. 4. Position of the physical wheel against simulated wheel (blue: simulation, red: physical).

3.6. Scenarios

Three scenarios were designed in our simulator: rural, city, and highway. All scenario maps were imported from the Carla environmental asset with minor modification. In addition, they were designed so as to guide users to gradually get used to the interaction with the AV, understand its capabilities, and start building confidence in it.

3.6.1. Rural

The rural scenario is a representation of the suburban environment, consisting mostly of trees, shrubs, one-lane country roads, and stop signs at intersections. This scenario serves as a familiarization step, in which the participants try to actively control the vehicle with the steering wheel and pedals in the manual mode, and let the vehicle drive itself in the autonomous mode. Since the rural scenario enforces simple road conditions and low vehicle speed, participants can get used to the simulation environment and vehicle controls in a relaxed setting. No other vehicles are added into the map to help keep the tutorial clean and simple (see Fig. 5).

Fig. 5. Rural scenario in the first-person driver's seat view

3.6.2. City

The city scenario is populated with buildings, traffic lights, and complex road crossings. In this scenario, participants are not required to drive, and are asked to turn on the autonomous mode and watch the vehicle navigate by itself. The predefined route will guide the AV to go through several conditions such as sharing the road with conventional vehicles, merging at an unprotected intersection, waiting for traffic signals, and yielding to pedestrians. Participants can resume manual control at any time if they feel unsafe or would like to handle an emergency situation. The goal of this scenario is to show the capabilities of AVs in a complex city environment to help participants further increase understanding and trust (see Fig. 6).

Fig. 6. City scenario in the first-person driver's seat view.

3.6.3. Highway

The highway scenario is a three-lane express road with no crossings and cyclists (see Fig. 7), and several NPC vehicles are added with varying velocities and driving behaviors. In this scenario, participants can switch freely between manual and autonomous driving. In addition, the AD supports three different behaviors: cautious, normal, and aggressive. Different driving behaviors have different acceleration, brake, and velocity preferences. In all cases, the AV can automatically take over another vehicle that is driving at a lower speed. Participants are encouraged to actively use AD to experience its different driving behaviors, and they can change the behavior using the up & down buttons on the steering wheel (see Fig. 3). The three AD driving behaviors are not available in the previous scenarios primarily for two reasons. First, in the rural and city scenario, the vehicle has a relatively low speed limit and different driving styles will not show much difference. Second, we want to increase the complexity of control one step at a time so that users do not get overwhelmed and withdraw from the simulator.

Fig. 7. Highway scenario in the first-person driver's seat view. Current autonomous driving mode is set to cautious, other available options: normal, aggressive.

4. Experiment

4.1. Participants

To test the validity of our simulator, we recruited 36 participants via email and social media for a test drive. To qualify for the study, the participant must meet all of the following requirements: be older than 18 years old and less than 75; have a valid driver's license and at least three months of independent driving experience; does not have a police-reported crash within the last year; have normal or correct-to-normal vision and hearing (contact lens allowed); does not have a history of migraine headsets, claustrophobia, or motion sickness; is not currently pregnant; and have no prior riding experience with autonomous vehicles (which does not include cruise control, lane keeping assist, forward collision warning, emergency break, and other ADAS features). In addition, participants were carefully selected so that most of them do not have a professional understanding of AVs.

Our participant group consisted of 18 males, 18 females and had a mean age of 25.5 years. The participants were compensated with a $25 Amazon gift card for taking part in the study. If they decide to quit in the middle of the study for any reason, they still get compensated. This study was approved by the Institutional Review Board at the University of Pennsylvania (IRB Protocol#: 850824) and all participants gave their informed written consent.

4.2. Survey

The effectiveness of our simulator was measured through the survey instrument. Before the simulator, participants were asked to assess their understanding of AVs, and the choices included: "I hear about it from the news and social media but know little about it", "I know the vehicle uses sensors and artificial intelligence but have no understanding of the technology", "I have a basic understanding of the sensor data and algorithms running on an autonomous vehicle", "I have a decent understanding of the algorithms and software stacks running on an autonomous vehicle". The next part was AV ratings and included questions from five different categories: perceived risk (PR), perceived usefulness (PU), perceived ease-of-use (PE), trust (TR), and behavioral intention (BI). Each category had three questions while the categorization was not explicitly shown (see Table 1). The fifteen questions were adapted from the survey design in (Dirsehan, & Can, 2020; Yuen, Wong, Ma, & Wang, 2020; Zhang, Tao, Qu, Zhang, Lin, & Zhang, 2019; Choi, & Ji, 2015) and modified to fit the need of this study. They used the five-point Likert scale ranging from *1=Strongly Disagree* to *5=Strongly Agree*.

After the simulator study, the fifteen questions were asked again to measure any attitude change. Participants were given a different sheet and could not refer to their previous answers. The remaining questions were all qualitative, including participants' general idea on using a driving simulator, their preference on the AD driving behavior, and their additional questions and comments for the study.

4.3. Procedure

Participants who contacted us and met the requirements were invited to our research lab. Upon arrival, they read and signed the consent form, and filled in the first part of the survey. Then, they watched a three-minute video introducing the five levels of automation which was a plain explanation of the vehicle's capabilities (Geospatial World, 2018). With this background information, the researcher then explained that the simulator AD was set at Level 4. After that, the participants took a seat in the simulator setup (see Fig. 8) and tried all three scenarios as described in the previous section. In each scenario, they were asked to drive along a predefined route, but with the freedom to switch between the manual and autonomous mode at any time. After the participants finished all three scenarios, we gave them the second part of the survey, and answered any additional questions, comments, or concerns.

Table 1
Fifteen Quantitative Survey Questions.

PR1	I am worried about the safety of autonomous driving technology.
PR2	I am worried about the interaction of an autonomous vehicle with conventional vehicles.
PR3	I am worried that autonomous driving system failure or malfunction may cause accidents.
PU1	Using an autonomous vehicle will allow me to conduct non-driving related tasks.
PU2	Using an autonomous vehicle will increase my driving safety and efficiency.
PU3	Using an autonomous vehicle will be useful when I am physically or mentally impaired.
PE1	Learning to operate an autonomous vehicle would be easy for me.
PE2	Interacting with an autonomous vehicle would not require a lot of my mental effort.
PE3	I think it is easy to get an autonomous vehicle to do what I want to do.
TR1	I believe that autonomous vehicles can take me safely to my destination.
TR2	I believe that autonomous vehicles can handle most traffic conditions.
TR3	I believe that autonomous vehicles are as reliable as my own driving.
BI1	I intend to ride in an autonomous vehicle in the future.
BI2	I expect to purchase an autonomous vehicle in the future.
BI3	I plan to introduce autonomous vehicles to my family and friends.

Fig. 8. Simulator demonstration: left monitor shows Carla server first person driver's seat view; right monitor shows the Carla client third-person tracking view.

5. Analysis

5.1. Initial Analysis

Of the 36 participants, 10 stated that they had a limited understanding of AVs, 17 answered that they knew the vehicle uses sensors and artificial intelligence, and 9 answered that they had a basic understanding of the different sensors and data running on an AV. The means and standard deviations of the 5 categorical measurements were computed and shown in Table 2. For each category, the value is an unweighted average of its 3 questions. In addition, Cronbach's α coefficient was computed to validate the internal consistency of each category. The results have shown that the average ratings for all categories improved after the simulator demonstration, which means that participants' opinions towards AVs in general shifted towards the positive direction.

Table 2
Mean, Standard Deviation, and Cronbach's Alpha of the Five Categorical Measurements.

	Pre Simulator			Post Simulator		
	M	SD	Cronbach's a	M	SD	Cronbach's a
PR	3.44	0.75	0.69	2.95	0.84	0.82
PU	3.53	0.65	0.03	3.90	0.79	0.67
PE	3.35	0.73	0.57	3.72	0.71	0.52
TR	3.12	0.77	0.75	3.60	0.78	0.75
BI	3.63	0.84	0.78	3.98	0.76	0.82

5.2. Wilcoxon Signed-Rank Test

To verify that the changes in participants' attitude were statistically significant, a Paired-Samples T Test was proposed. However, a Chi-Square Test showed strong evidence ($p < 0.01$) that the difference between the experimental data was not normally distributed and violated the test assumption. Therefore, a Wilcoxon Signed-Rank Test was applied to test the data significance. It is shown that after the simulator experiment, there was a significant decrease in PR ($N = 33, p < 0.05$), a significant increase in PU ($N = 31, p < 0.05$), a significant increase in PE ($N = 28, p < 0.01$), a significant increase in TR ($N = 27, p < 0.01$), and a significant increase in BI ($N = 21, p < 0.01$). The significant improvement in all categories confirmed our hypothesis on the effectiveness of the simulator.

5.3. Internal Consistency

The Cronbach's α coefficient showed different results before and after the simulator experiment but remained mostly consistent for each category. PR initially received a score of 0.69 and then increased to 0.82, indicating that participants' evaluations on risk became better aligned across different perspectives. PE received a score of 0.52 before and 0.57 after, showing that the internal connection among the questions is only moderate and does not change much due to the simulator. TR received a score of 0.75 both before and after the simulator study, meaning that trust is a consistent measure and can be bonded to a certain standard. Similarly, BI received high scores around 0.8, suggesting that participants' opinions were aligned in terms of purchasing, riding, or introducing an AV. The counterintuitive part lied in PU, which initially showed no connections among the questions with a score of 0.03 but increased to 0.67 after the simulator trial. To explain this, we took a deeper look and found that many participants originally gave a score of one for PU1, which asked about AV assisting them conducting non-driving related tasks. In comparison, they gave high scores for PU2: AV helps increase driving safety and efficiency, and PU3: AV helps drivers that are physically and mentally impaired. The high inconsistency showed that although participants agreed on AD's safety assistance, they were concerned in handing over control and focusing on other tasks. After the simulator, however, participants built a sense of what AD felt like and became more confident in its performance, which helped align the measures and contributed to a higher Cronbach's α.

6. Discussion

6.1. AD Behavior Choice

After the highway mode, participants were asked about whether they like to stick to one AD behavior or use all three behaviors (cautious, normal, aggressive) interchangeably. About half of the participants stated that they prefer the availability of all three behaviors, so that they could decide which one to use based on the time, safety, and comfortability requirement. Another group answered that it would be nice to have all three choices, but they would almost always use the aggressive one. The remaining participants said that they just want aggressive behavior, and according to them, if the AD was designed to prioritize safety, why not drive as fast as you can?

6.2. Driver's Background

We also found that drivers' evaluations on AVs were dependent on their own perceived driving skills. Participants who claimed to have a lot of driving experience tended to not trust the AD: they described the AD as safe but rigid, and definitely not a match for their own driving. On the contrary, participants who drove little and were concerned with their own driving safety showed higher interest in AD and praised its safety measure. From this observation, we can reasonably infer that people who are more dependent on AD and who can benefit most from it will be more willing to embrace the technology, while people who heavily relied on and enjoyed their own driving would be reluctant to accept it.

6.3. Simulator for AV Demonstration

The researchers discussed with the participants about the use of the simulator for AV demonstration. A typical example would be at auto dealerships, and most participants stated that they definitely want some simulation experience in helping them make the choice. While it is agreed that driving simulators cannot provide the physical motion and the sense of alertness as in real traffic, they come with their unique advantages. First, a driving simulator is not constrained by the available conditions during a test drive, and grants the flexibility to adjust weather, lighting, traffic, and geographic parameters. Second, the simulator experience can take an extensive period for a thorough evaluation of the system with zero damage and cost. Third, a real test drive may not always be feasible, for instance, during an auto show, a tech exhibition, or an academic conference, while the simulator is much easier to carry around and can be set up at different places. Overall, driving simulators, with unique advantages, can complement the goal of AV demonstration.

6.4. Simulator for AV Education

Driving simulators can also be used for driver's education. There are two cases: those with a valid driver's license and those with not. During our study, many participants pointed out that just because someone holds a valid driver's license does not mean they should be legally allowed to use an AV. Currently, due to limited knowledge and experience, drivers tend to blindly trust or untrust AVs and often use them with overconfidence or little confidence. In this case, AV specified training and qualification is recommended, and a driving simulator can make a decent platform. For those without a driver's license, a simulator can also be a good tool to practice driving skills, and the user can learn to drive a conventional vehicle while interacting with the AD features at the same time.

7. Limitation & Future Work

7.1. Simulation Environment

Our Carla-based simulator, despite its vivid environment, is not an exact capture of the real world. In order to achieve higher effectiveness on AV demonstration, the simulator must support high-fidelity, which requires its elements to resemble the real world as much as possible. While such design can be challenging, it is not unachievable. For example, in the release of Unreal Engine 5, games showed an unprecedented level of detail and interactivity which have made it hard to differentiate between the virtual and the real world. Since our simulator was built using the Unreal Engine 4, there is a lot of space for improvement.

7.2. User Interaction

Our AD ran in a black box and no decision information was presented to the driver. This is due to limited development time and the complexity to create a well-framed user interface. In the future, we would like to add an extra layer of animation and allow the user to use the touch panel like a real vehicle. The touch command can be achieved using the VR headset controller, just like any standard VR application. The vehicle's AD information can be extracted from the backend program and displayed in a user-accessible way. In addition, we can link our simulation platform to more favorable AD platforms such as Apollo and Autoware using the ROS bridge. By doing that, we can take advantage of their well-designed software stacks while maintaining the uniqueness of our immersive VR environment.

7.3. Mixed Reality Environment

The G29 steering wheel and pedal set is good for vehicle control but still somewhat different from a real car. In the next stage, we plan to move from the virtual reality simulation into the mixed reality framework, which means that the participants will sit in a real car, wearing a headset, observe everything inside the car, and make controls using the real steering wheel and pedals. The vehicle will be surrounded by greenscreen, and the view through the windshield will be replaced by the simulation environment. In this case, users can drive the vehicle in the simulation world but will remain stationary at all times.

7.4. Participants

Our small number of participants cannot represent all age, gender, and population groups. The future study requires a greater number of participants with varying backgrounds to achieve more comprehensive and objective analysis.

8. Conclusion

We presented in this work a virtual reality driving simulator and an interactive driving experience to improve people's understanding and trust of autonomous vehicles. To that effect, we adapted the open-source driving simulator Carla and designed several driving scenarios. A study with 36 participants showed that our simulator successfully improved participants' attitude towards autonomous vehicles in terms of perceived risk, perceived usefulness, perceived ease-of-use, trust, and behavioral intention. We also presented the application of a simulator at driving schools, auto dealerships, and other places. Limitations existed in terms of the hardware, software, and sampling, which we aim to improve in the future. Overall, the driving simulator and human study presented in this paper act as an innovative, pioneering effort to promote safe autonomous vehicle education, training, and demonstration.

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