Effects of External Human Machine Interfaces on Automated Vehicles' Communicative Interactions With Human Drivers

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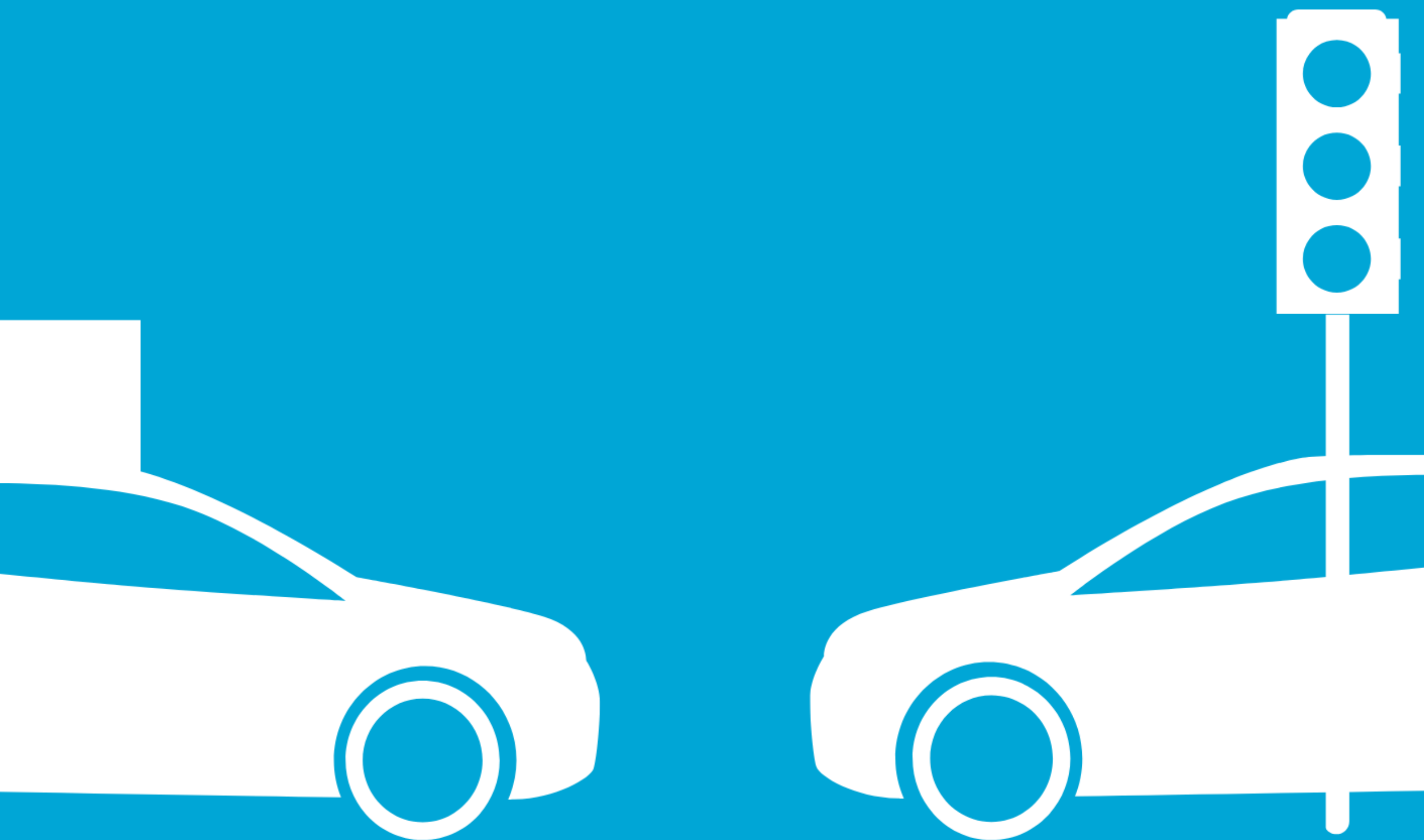

Delft University of Technology

Effects of External Human Machine Interfaces on Automated Vehicles' Communicative Interactions With Human Drivers

by

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Preface

On August 16, 2019, I crossed India's border for the first time and arrived in the Netherlands. As I came out of the airport, signboards slowly changed from English to Dutch. Everything started to look unfamiliar. As I board the intercity to Delft, I was afraid to sit on a seat. I did not know when to get off the train, and I was shy to ask for help. A confident Dutch woman came up to me and helped me out. Her confidence assured me that everything was going to be fine thereafter.

My journey at the TU Delft is not just about pursuing a master’s degree. It is about building self-confidence. None of the academic attainments, such as the Holland Scholarship, honours programme, the extra 26 ECTS, built my confidence. However, my master thesis has given me with a different perspective. I do not build self-confidence based on the attainments but from the work I do, wholeheartedly. Sometimes, the past work does not provide me with the boost in unforeseeable situations. My committee members have hinted at a solution. Funnily, I put it as a dialogue from a movie (i.e., 3 idiots):

Rancho: …I understood that this heart scares easily. You have to trick it; however big the problem is. Tell your heart, 'Pal, all is well. All is well.'

Raju: Does that solve the problem?

Rancho: No, but you gain the courage to face it…

This realisation, this thesis and this journey would not be complete without the support and guidance of my committee members. I would like to thank my committee for their academic guidance and, specifically, for teaching lessons for work and life. With her empathetic actions, Haneen Farah has brought a significant difference in how I work and interact with others. Her boundless enthusiasm, guidance and helping nature has inspired me to work wholeheartedly that has positive implications for my academic and personal life. Bart van Arem has amazed me with how he strikes a balance between flexibility and discipline. He inspires me to have work-life efficiency. I had one-to-one interactions with Joost de Winter for less than an hour or two in the whole project duration. His past work, constructive feedback and out-of-the-box ideas have made sure that he leaves an impact with minimal interaction. He inspires me to be creative and effective with my work. Anastasia Tsapi offers a warm environment, where interactions with her feel less formal and more friendly. She has taught me a lot of professional tips and tricks in a friendly manner. Yongqi Dong has taught me to be effective and efficient with my words during meetings.

A special thanks to Marco van Burgsteden (from CROW) and Evert Klem (from RHDHV) for briefing me on the challenges faced by the road authorities. I thank Solmaz Razmi Rad for sharing her knowledge on Unity 3D and driving simulator.

My deepest gratitude goes to my family, Mahesh Lingam (my father) and Sridevi Lingam (my mother), who provide me with immense love and support even outside their comfort zone. More than me, they believe in my goals which gives me constant strength. I thank my best-friend Sainath and my friends and career advisors Narayana, Nagarjun and Kubair, who made this journey meaningful and enjoyable. I sincerely thank my friends in the Netherlands and India. They provided me with wonderful memories and experiences.

Shiva Nischal Lingam

Delft, November 2021

Executive summary

Introduction

Driving involves communicative interactions where human drivers use communication signals (e.g., eye contact, hand gestures) to negotiate their right of way and drive safely on the road. The introduction of automated vehicles (AVs) in mixed-traffic environment, where human drivers will interact with AVs, will affect the nature of these communicative interactions. AVs and human-driven vehicles (HDVs) use different communication forms (e.g., vehicle-to-vehicle communication between AVs vs eye-contact between humans). This may affect the social acceptance of AVs, traffic safety and efficiency in mixed-traffic environment. In order to increase the social acceptance of AVs and reduce potential misinterpretation of AVs intent among human drivers, research should investigate whether AVs need to clearly convey their intent when interacting with HDVs. A possible solution is to explore the potential of external human machine interface (eHMI) to improve the communicative interactions between AVs and HDVs.

Conclusions from previous literature on AV-pedestrian and HDV-HDV interactions vary with respect to the need of eHMIs for AVs in mixed-traffic environment. Furthermore, there are limited studies which have explored the need for eHMIs in AV-HDV interactions. In addition, the effect of eHMIs might differ depending on their placement (e.g., on vehicle or infrastructure). No concrete recommendation is available in the literature about the standard placement of eHMIs and the impact on their usability and realism. These gaps introduce ambiguity among the stakeholders, who might develop diverse eHMI designs that lead to unsafe or inefficient traffic interactions. This research makes an effort to fill those gaps. First, this research investigates the effects of AVs' eHMI presence on human drivers' perception and behavior when interacting with AVs. Second, it explores the effect of eHMI placement (i.e., on vehicle or infrastructure) on human driver interactions. The eHMI concepts were inspired from traditional traffic signals. The use case of this research is an unsignalized T-intersection on a distributor road outside an urban area with a speed limit of 80 kmph. In particular, human drivers perform right-turn maneuvers at unsignalized T-intersections.

The main research question of this study is:

What is the effect of eHMIs on AVs' communicative interaction with human drivers who perform a right-turn maneuver at unsignalized T-intersections?

In order to answer this research question, a driving simulator experiment was designed and the collected data were analysed in order to gain insights into the eHMI effects on human driver interaction with AVs.

Method

This research aims to study communicative interaction of AVs with HDVs using driver perception (e.g., trust, user acceptance, emotions) and behavior (e.g., approaching speed, crossing decision, critical events). Driver perception variables represent the human driver experiences and judgements of eHMIs in the AV interactions. Driver behavior variables measure the human driver's decisions and actions when interacting with AVs that communicate their intent using eHMIs.

In this research, the AVs communicated their intention with HDVs based on one of the following three eHMI conditions: baseline, eHMI on the vehicle, and eHMI on infrastructure. The baseline condition did not include any eHMI for the AV. eHMI on vehicle was in the form of a display cube on top of the AV roof which displays the AV intention (see Figure 1). eHMI on infrastructure delivered AV intent through signalling devices fixed at the intersection (see Figure 2). The eHMI signals were conveyed through colors (e.g., purple and green). Purple represented an AV intent to cross before the HDV and therefore requested the HDV to yield, whereas green exhibited the decision of AV to yield and cross after the HDV.

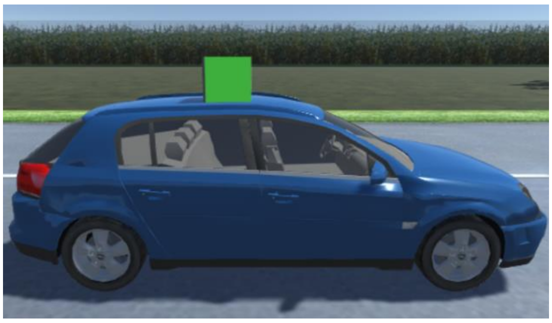

Figure 1: AV with an eHMI in the form of a cube. The eHMI exhibits green to signal HDVs to cross.

Figure 2: eHMI on the infrastructure where signals communicate AV intent. For instance, AV requests the HDV to cross first through a green signal.

The driving simulator experiments were conducted in July 2021. In total, 46 participants (31 Males; 15 Females) took part in the experiment. The majority of the participants had at least a bachelor's degree in science. Each participant drove the three defined scenarios: baseline, eHMI on the vehicle, and eHMI on infrastructure. The three scenarios were randomly assigned. In each scenario, the participants were asked to reach a destination by interacting with AVs at T-intersections. Before reaching an intersection, the participants were instructed to reach a trigger location at 50 kmph (see Figure 3). This trigger activated the AVs and the eHMIs which

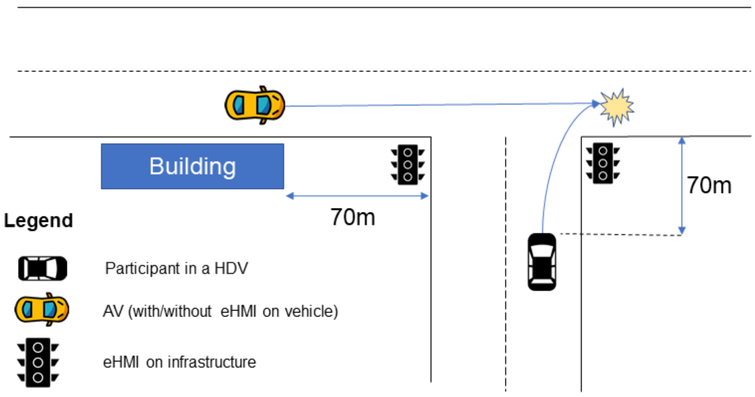

Figure 3: AV starts to move and exhibit eHMI signals when HDV reaches a trigger location (i.e., 70 m from intersection) at 50 kmph.

were visible to the participant from that point. After crossing the trigger location, the participants were allowed to make independent driving decisions during their interaction with the approaching AV from the intersecting road. The approaching AVs differed in their driving styles. Some AVs were designed to give the right of way to the participants, while others were designed not to give the right of way. The driving style of AVs was randomized within and across the scenarios. The participants interacted with the AV at 10 interactions in each scenario, where five AVs were designed to yield and the other five were designed not to yield the right of way. At the end of each scenario, the participants were requested to fill the perception questionnaire based on their driving experience in the scenario. The observations might depend on the visibility of AVs and its eHMIs to the participant.

Analysis and results

In order to understand the effect of eHMIs on driver perception and behavior, statistical analysis (e.g., descriptive and inferential statistics) and modelling (e.g., Generalized linear mixed modeling) were performed on the measured variables. Three models consisting of preference, critical events and crossing time were developed. The preference model was built to understand the eHMIs and drive perception implications for social acceptance of AVs. Critical events model and crossing time model predicted the combined effect of eHMIs, AV driving style and driver perception on traffic safety and efficiency of the AV-HDV interactions, respectively.

Significant differences in perception and behavior were found in pairwise comparisons between the eHMI conditions as shown in Figure 4 and Figure 5, respectively. Higher pleasure and lower arousal scores were reported by participants with eHMIs compared to the baseline. The lowest arousal score was observed with the eHMI on infrastructure. Trust and user

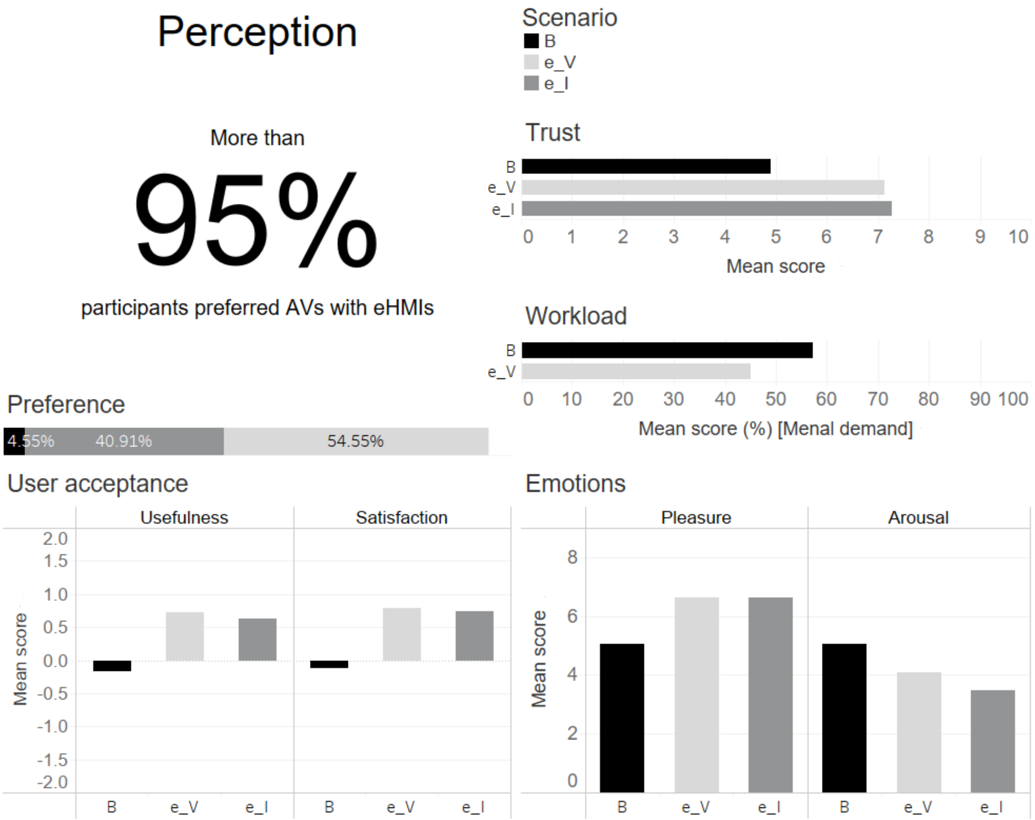

Figure 4: A dashboard illustration of drive perception results that are significant at p-value < 0.05. Among the scenarios, B, e_V and e_I represent baseline, eHMI on vehicle and eHMI on infrastructure, respectively.

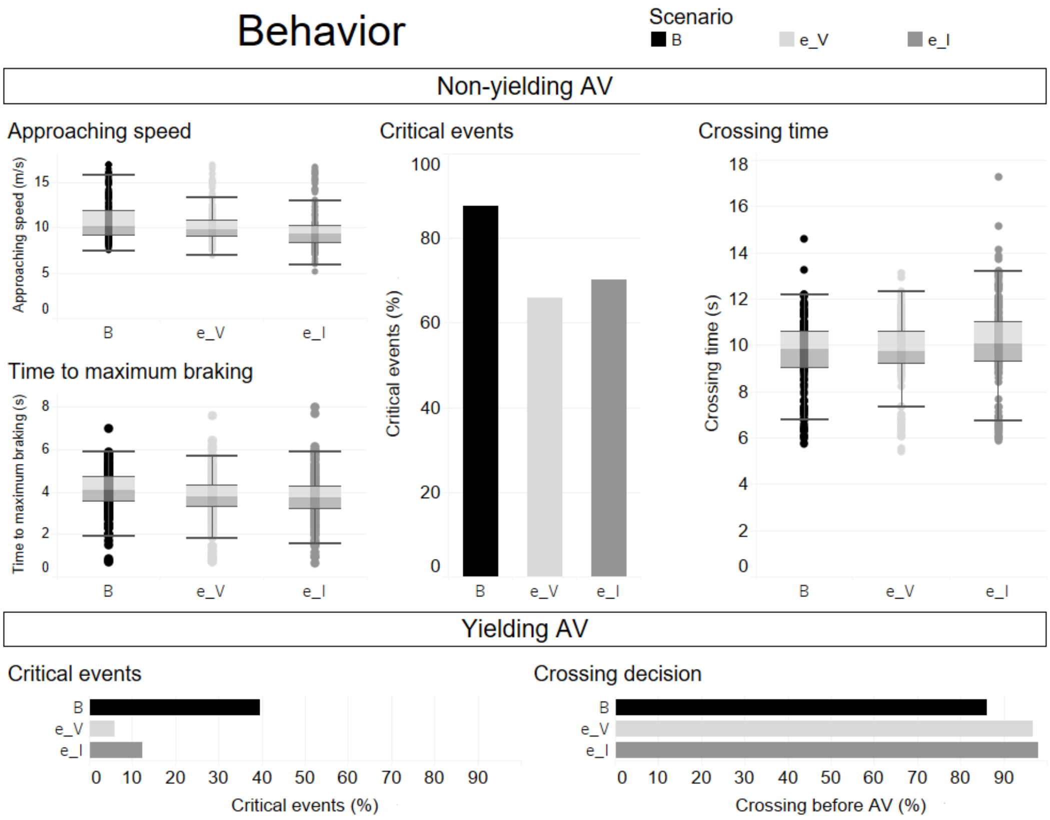

Figure 5: A dashboard illustration of driver behavior results that are significant at p-value < 0.05. The results are differentiated for AV driving style (i.e., non-yielding and yielding). Among the scenarios, B, e_V and e_I represent baseline, eHMI on vehicle and eHMI on infrastructure, respectively.

acceptance scores were higher for AVs with eHMIs than baseline. Further, more than 95% of participants preferred AVs that communicate intent with at least one form of eHMI. Preference for AVs, trust and user acceptance were not significantly different between the two conditions of the eHMIs (i.e., on vehicle or infrastructure). Regarding the workload measures, mental demand of participants was lower with the eHMI on vehicle than the baseline.

The effect of eHMIs on driver behavior variables was greater in interactions with non-yielding AVs than yielding AVs. The participants had lower approaching speed, time to maximum braking and proportion of critical events (i.e., Post Encroachment Time between AV and HDV < 3s) with AVs that exhibit non-yielding intention with eHMIs compared to baseline. Participants took significantly less crossing time during the interaction with AVs that communicate non-yielding intent via eHMI on vehicle than on infrastructure.

More participants are compliant to yielding AVs with eHMIs than baseline. No significant differences were observed in the crossing decision of participants between the two eHMI conditions. In addition, the participants were involved in a lower proportion of critical events for eHMI conditions than baseline. In particular, lower critical events were observed for yielding AVs with eHMI on vehicle than infrastructure.

The results of the three developed models are depicted in Figure 6. The preference model results show that eHMIs are likely to increase preference for AVs compared to baseline scenario without eHMI. In addition, the perceived usefulness of AVs' communication system is likely to increase preference for AVs. The critical events model illustrates that eHMI on vehicle has a higher chance to reduce critical interactions between AVs and HDVs, when compared to baseline. However, eHMI on infrastructure does not have a significant effect in the critical events model when compared to baseline. Furthermore, a yielding AV is likely to reduce critical interactions with HDVs than a non-yielding AV. On the other hand, the crossing time model predicts that the effects of eHMIs on the crossing time are not different from the baseline. As HDVs wait for the AVs to pass first, a non-yielding AV is likely to increase the crossing time for HDVs than a yielding AV. Perception and behavior variables such as usefulness, arousal and maximum deceleration are likely to reduce the crossing time of participants.

Models

Preference

Intercept		-3.67
Scenario	Baseline	0.00
	eHMI on infrastructure	2.61
	eHMI on vehicle	3.05
Usefulness		0.88

Coefficient
-3.67 3.05

Critical events

Intercept		1.71
Scenario	Baseline	0.00
	eHMI on vehicle	-1.76
AV_DS	Non-yielding	0.00
	Yielding	-3.87

Coefficient
-3.87 1.71

Crossing time

Intercept		2.13
AV_DS	Non-yielding	0.00
	Yielding	-0.14
Arousal		-0.02
Usefulness		-0.02
Maximum	deceleration	-0.03

Coefficient
-0.14 2.13

Figure 6: A dashboard depiction of model results. The reported results in the models are significant at p-value < 0.05. AV_DS represents automated vehicle driving style. Reference values are expressed as '0.00'.

Discussion and conclusion

Overall, the findings show that the eHMIs of AV have a significant effect on driver perception and behavior while performing right-turn maneuvers at unsignalized T-intersection. eHMIs seem to have a positive effect on driver perception in terms of driver emotions, trust and user acceptance. In particular, eHMI on vehicles reduces the mental demand, and eHMI on infrastructure increases the calmness experience of the drivers. These observations explain that explicit information helps the road user to understand AV intent clearly and make decisions with more certainty at the T-intersections. As a result, drivers prefer AVs with eHMIs over no eHMI. These observations imply that eHMIs can improve the social acceptance of AVs.

eHMIs affect the driver behavior at a greater level during the different crossing stages in the interactions with non-yielding AVs than with yielding AVs. For yielding AVs, eHMIs have a significant effect only on the crossing stage variables. Whereas in interactions with non-yielding AVs, eHMIs have a significant effect on the variables in pre-crossing, crossing, and post-crossing stages. A potential explanation is that the non-yielding AVs introduce uncertainty in the decision-making of participants. In other words, the effect of eHMIs on driver behavior increases with uncertainty in the interactions. This is reflected as a positive effect of eHMIs on driver emotions, trust and user acceptance.

In uncertain interactions, the eHMIs decrease the drivers' time to maximum braking and approaching speed which further reduces the critical interactions between HDVs and AVs. The critical events model predicts that AV with eHMI on vehicle reduces the critical interactions compared to no eHMI condition, which implies increased traffic safety at T-intersections. This could be due to lower mental demand with eHMI on vehicle. However, no such effects were found for the eHMI on infrastructure.

eHMI on infrastructure, which is inspired by traffic signals, leads to calmer experience and persuades drivers to further lower their approaching speed which increases the crossing time. However, the crossing time model predicts no eHMI effects on the efficiency of AV-HDV interactions at T-intersections. Driver crossing decisions show that eHMIs improve driver compliance which in turn has positive implications for efficiency and safety of the AV-HDV interactions.

In conclusion, eHMIs have the potential to enhance communicative interactions of AVs with HDVs at unsignalized T-intersections. In particular, eHMI on vehicle can reduce the critical interactions between AVs and HDVs. No significant differences were observed between the eHMI conditions for the acceptance of AVs and efficiency of the AV-HDV interactions.

Recommendations

The results of this research show that eHMIs have the potential to improve traffic safety at T-intersections and the acceptance of AVs among human drivers. Accordingly, recommendations are provided to various stakeholders.

This research studies a novel (directional) eHMI concept (see Figure 1) that could contribute to scalability and higher resolution of communication to other road users. AV manufacturers are recommended to further investigate and optimise the design of directional eHMI to make it suitable for different on-road interactions (e.g., merging on highways, shared space, X-intersection).

Road authorities are recommended to collaborate with AV manufacturers in developing industry standards for eHMIs. For instance, such collaboration could aim at standardizing the modality and nature of the message (i.e., eHMI signal) that is effective and acceptable among road users. As the traffic light design provided a calmer experience for the participants in this research, road authorities could explore the methods for successful integration of eHMIs in advanced traffic controllers (e.g., intelligent traffic light installations).

The difficulty arises when human drivers do not show acceptance and trust in AVs despite their benefits. This difficulty could increase critical interactions. Our research explored two eHMI concepts that could improve driver trust and acceptance of AVs. The participants preferred AVs with eHMIs as the design was simple and intuitive. Hence, road authorities and AV manufacturers are recommended to investigate eHMI designs that are simple, intuitive and acceptable among road users.

Our findings show that eHMIs could reduce driver workload and positively affect driver emotions and acceptance of AVs. Modelling results illustrate that the eHMI on vehicle has the potential to reduce critical events at T-intersections, which benefits society. For the betterment of society, policymakers are recommended to carry out a cost-benefit analysis to quantify the eHMI effects for society at large.

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Abbreviations

AV	Automated Vehicle(s)
eHMI	External Human-Machine Interface(s)
eHMI_V	External Human-Machine Interface on Vehicle
eHMI_I	External Human-Machine Interface on Infrastructure
GLMM	Generalised Linear Mixed Model
HDV	Human Driven Vehicle(s)
ODD	Operational Design Domain
OEM	Original Equipment Manufacturer(s)
PET	Post Encroachment Time
SDS	Semantic Differential Scale

1 Introduction

Driving is a social task where drivers use diverse forms of communication to reduce uncertainties and crashes during interactions with other road users (Lamas, Burnett, et al., 2014; Rasouli et al., 2018; Wolf, 2016). These interactions are referred to as communicative interactions that could differ with the advent of automated vehicles (AVs), especially driverless AVs. According to Bansal & Kockelman (2017), adoption of AVs range between 24% and 87% in the United States by 2045. During the early adoption periods, AVs need to interact with human-driven vehicles (HDVs) which increases uncertainty on roads. A possible reason is that AVs create a social gap as the communication form is different to humans (Rasouli et al., 2018; Vinkhuyzen & Cefkin, 2016). For instance, AVs could communicate through vehicle-to-vehicle communication; however, human drivers use hand gestures and eye contact (among other forms) to communicate with other HDVs. Due to the differences in communication, human drivers are likely to misinterpret AVs' intent. Goodwin (2020) mentioned that 3 out of 4 Americans think that driverless vehicles are not ready for roads because the road users do not clearly understand the AV intent. Misinterpretation between road users may affect social acceptance of AVs, traffic safety and efficiency (Rettenmaier et al., 2019). These effects are likely to pronounce in a mixed traffic environment with different road users.

Previous research on communicative interactions among HDVs illustrate that drivers use implicit signals (e.g., yielding, non-yielding) and explicit signals (e.g., gestures, eye-contact, headlights) to communicate their intent (Ba et al., 2015; Dietrich, 2018; Kitazaki & Myhre, 2015; Portouli et al., 2019; Risto et al., 2017; Uttley et al., 2020). Most of the previous studies on communicative interactions between HDVs are divided on their recommendations for the development of communication signals in AVs (Ba et al., 2015; Dietrich, 2018; Kitazaki & Myhre, 2015; Portouli et al., 2019; Risto et al., 2017; Uttley et al., 2020). Some authors suggest that implicit signals are enough to communicate AV intent (Lee et al., 2020; Risto et al., 2017; Uttley et al., 2020); whereas, others argue that external human machine interface (eHMI; along with implicit signals) communicates a clear intent and resolves deadlock situations at intersections and narrow roads (Dietrich, 2018; Kitazaki & Myhre, 2015; Portouli et al., 2019; Rettenmaier et al., 2019). Previous studies on HDV-HDV interactions suggest that eHMIs have the potential to improve social acceptance of AVs, traffic safety and efficiency in the mixed traffic environment (Dietrich, 2018; Imbsweiler et al., 2018; Portouli et al., 2019). However, there are limited studies that investigate the effect of eHMI presence on AV-HDV interactions.

In addition, no concrete recommendation is available about the standard placement of eHMI which affects the realism and usability of AV communication on roads (Dey et al., 2020; Mahadevan et al., 2018). In a literature review, Dey et al. (2020) explained that more than 50 studies investigated eHMI concepts on vehicles, whereas only one study explored eHMI on infrastructure. With regard to eHMI placement, each concept has both advantages and disadvantages. For instance, eHMI on vehicles requires less visual scanning for the human driver to know the AV intention compared to eHMI on infrastructure. On the other hand, eHMI on infrastructure exists in the vision line of driver and conveys AV intention even when the visibility of AV is occluded. Previous research rarely discusses the optimal location for eHMIs and its effects on human driver interactions. This could raise the gap in distinguishing the responsibilities of stakeholders (e.g., AV manufacturer and road authority) for developing and maintaining the eHMIs. These gaps could lead to the development of diverse eHMI designs for a traffic interaction. No standardization of an eHMI concept might increase traffic crashes and inefficiency. Hence, there is a need to investigate the effects of eHMI placement in mixed-traffic environment.

In order to meet the need, research must find out whether an eHMI is necessary for AVs in communicative interactions with human drivers to reduce misinterpretation among the drivers. In that event, further analysis is required to understand the effect of eHMI placement on human driver interactions with AVs. In order to find the optimal location of eHMI, the effects are to be studied on social acceptance of AVs, traffic safety and efficiency.

1.1 Scope of the research

This research primarily investigates the impact of eHMIs on AVs' communicative interactions with HDVs at T-intersections. The communicative interactions are measured with driver perception and behavior in the interactions with AVs that communicate with eHMIs. A simulator experiment is implemented to understand if eHMI presence influences interactions with human driver. In addition, the research explores the effect of eHMI placement (i.e., eHMI on vehicle or infrastructure) on driver perception and behavior in the interactions. The research utilizes modelling techniques to understand the implication of eHMIs on social acceptance of AVs, traffic safety and efficiency. However, our research does not focus on the design aspect (e.g., shape, size, message format) of an eHMI. Our research assumes that AVs may or may not follow right-hand rule at the intersections. The focus is on one-to-one interaction between HDVs and AVs. These interactions are expected to occur in the early phases of automation. The environment of this study includes a bi-directional distributor road (with a speed limit of 80kmph) with unsignalized T-intersections, where the human driver takes a right turn and interacts with an approaching AV on the left side.

1.2 Societal impact

Through a better understanding of communicative interactions between AVs and HDVs, this research contributes to the following user groups:

Scientific community – Scientific research could involve social aspects of the driving context (e.g., communication), besides human psychology, to study mixed traffic interactions, and contribute to traffic efficiency and safety. The above aspects support the development of human-like AVs and meaningful human control. Our research could help relevant scientists to make better predictions on the driving maneuvers and improve the predictability of human driving actions.

AV manufacturers – Many OEMs aim to make AVs socially acceptable among human users. Our research contributes to their goals by studying driver acceptance of AVs. In addition, this study investigates the human driver viewpoint that plays a vital role to understand driver needs for improving interactions with AVs. This could potentially reduce driver errors if AVs are designed, accordingly; which makes AVs safer to interact.

Road authority – Our research involves a novel concept, eHMI on the infrastructure, to enhance driver experience in interactions with AVs. Road authorities could make use of this concept to design infrastructure requirements for future AVs and improve road safety.

Policy makers – Our research contributes to social welfare by providing a possibility to reduce traffic crashes, save lives, congestion and fuel consumption. Furthermore, decision-makers could have an understanding on when to permit the AVs, that are more socially acceptable, on roads. Before the introduction of socially acceptable AVs, the policy makers need to consider the change in responsibilities and liabilities.

1.3 Thesis outline

The remaining chapters are outlined below.

Chapter 2 reviews the previous literature on communicative interactions to identify the research gap. The literature review provides the base to develop the conceptual framework for this research.

Chapter 3 argues the research need and defines the research questions. The chapter explains the conceptual framework for communicative interactions of AVs with HDVs. Furthermore, the chapter illustrates the hypotheses and research methodology.

Chapter 4 elaborates on the design of the research method, which includes driving simulator and questionnaires. In addition, the chapter explains the procedure for the participant recruitment and the experiment. Finally, the chapter discusses the lessons from the pilot tests.

Chapter 5 explains the collected data from the questionnaire and simulator. Further, the data is processed to handle the errors and outliers.

Chapter 6 elaborates the analysis method and reports the results. The analysis method includes preliminary analysis, learning effects and modeling.

Chapter 7 discusses the results and method, critically. The research questions are answered, and conclusions are drawn from the findings. The chapter ends with a discussion on the limitations of this research.

Chapter 8 provides recommendations to future research and the stakeholders that are responsible for the safe introduction of AVs.

2 Literature review

Automated vehicles are witnessing a significant development since the past decade (Chan, 2017). One of the reasons is that automotive manufacturers like Tesla, Toyota and Google made advancements in the AV technology (Raviteja, 2020). This technology is expected to shift the dynamics of transportation systems in terms of user acceptance of AV technology and mode choice (Chan, 2017); thereby affecting future mobility (Gruel & Stanford, 2016). Furthermore, AVs are expected to improve traffic flow, energy efficiency and traffic safety (Fagnant & Kockelman, 2015). These improvements encourage policymakers to consider AVs in the formulation of policies (Anderson et al., 2016). In spite of these benefits, AVs still have limitations. For example, AVs are not yet capable of communicating their intent with other road users, effectively (Vinkhuyzen & Cefkin, 2016). Human drivers, on the other hand, use vehicle-based signals such as deceleration and driver-based signals such as eye-contact to communicate with other road users (Möller et al., 2016). The current section reviews the literature on communicative interactions among human drivers, automated vehicles, and methods to measure communicative interactions between AVs and other human drivers.

2.1 Communicative interactions among human drivers

Drivers use communication in interactions, either to express cooperation or right-of-way in space-sharing conflict (Dietrich, 2018). Portouli et al. (2014, p. 1796) explained communicative interactions, “in cases of uncertainty […] drivers deliberately seek to interact with other drivers, so as to communicate their motion intent and coordinate towards a safe future motion plan.” In addition, the authors considered intentional social interactions as communicative interactions. In these interactions, drivers use informal rules and communication signals to safely interact with road users (Björklund & Åberg, 2005; Markkula et al., 2020; Wilde, 1976).

Previous research studied communicative interactions between human drivers and pedestrians for developing social AVs (e.g., Dey & Terken, 2017; Moore et al., 2019; Rasouli et al., 2018). These interactions generally occur at lower speeds and the road users have a possibility to communicate using body gestures. However, communicative interactions between the human drivers could be different and more difficult (Lamas, Harvey, et al., 2014; Renner & Johansson, 2006). Drivers are inside a vehicle, which provides a physical barrier to communicate their intents clearly to other drivers. Furthermore, roads with high speed provide less time to convey driver messages. These limitations might lead to improper interpretation of others’ intent, which causes crashes and traffic inefficiency (Risto et al., 2017). Hence, there is a need to study these interactions. Table 1 provides an overview of the literature that made an effort to understand communicative interactions between human drivers.

2.1.1 Methods

Previous research studied communicative interactions through a combination of methods; which creates a holistic understanding of cooperation between human road users (Dietrich, 2018). Common methods from the literature are observation protocol, running commentary, video analysis, survey, video-based experiment and driving simulator.

Observation protocol method involves experimenters positioning at a real-time location and manually observing communicative actions in the traffic using the protocol app (Dietrich, 2018; Lee et al., 2020; Uttley et al., 2020). This method captures the occurrence and sequence of implicit and explicit signals during communicative interactions in traffic (Dietrich et al., 2019). This method cannot measure driver perception and kinetic information of vehicle movements in communicative interactions.

Table 1: Overview of current studies on communicative interactions between human drivers

Authors (year)	**Title**	**Country**	**Method**
Ba et al. (2015)	The effect of communicational signals on drivers' subjective appraisal and visual attention during interactive driving scenarios	China	Driving simulator with on-road films, questionnaire
Dietrich et al. (2018)	interACT D.2.1. Preliminary description of psychological models on human-human and human-automation interaction	Germany, Greece, UK	Observation protocol, video analysis, verbal protocol analysis
Imbsweiler et al. (2018)	Insight into cooperation processes for traffic scenarios: modeling with naturalistic decision making	Germany	Questionnaire
Kauffmann et al. (2018)	"What makes a cooperative driver?" Identifying parameters of implicit and explicit forms of communication in a lane change scenario	Germany	Driving simulator
Kitazaki et al. (2015)	Effects of Non-Verbal Communication Cues on Decisions and Confidence of Drivers at an Uncontrolled Intersection	United States	Interview
Portouli et al. (2014)	Drivers' communicative interactions: on-road observations and modelling for integration in future automation systems	Greece	Verbal protocol analysis
Portouli et al. (2019)	Field observations of interactions among drivers at unsignalized urban intersections	Greece	Video-assisted observational study with retrospective commentary
Risto et al. (2017)	Human-vehicle interfaces: the power of vehicle movement gestures in human road user coordination	United States	Video analysis
Stoll et al. (2018)	Social interactions in traffic: the effect of external factors	Germany	Video-based experiment
Uttley et al. (2020)	Road user interactions in a shared space setting: priority and communication in a UK car park	United Kingdom	Observation protocol, video analysis
Vinkhuyzen & Cefkin (2016)	Developing socially acceptable autonomous Vehicles	United States	Video analysis, interview
Lee et al. (2020)	Road users rarely use explicit communication when interacting in today's traffic: implications for automated vehicles	United Kingdom	Observation protocol, questionnaire

Video analysis of on-road interactions enables researchers to understand communicative interaction patterns on roads in simple terms (Risto et al., 2017; Uttley et al., 2020; Vinkhuyzen & Cefkin, 2016). Video recordings are observed through a first-person or stationary ground-based cameras. First-person cameras (e.g., dashboard mounted cameras) capture communicative interactions from the viewpoint of the driver (Risto et al., 2017). On the other hand, a stationary-ground based camera positioned at a bird view provides an overview of multiple interactions from different vehicles (Portouli et al., 2019;

Risto et al., 2017). Limitations of this method include privacy concerns, homography and image distortion in a few cases (Portouli et al., 2019). Video analysis does not capture driver perception in communicative interactions.

Portouli et al. (2014, 2019) implemented verbal protocol analysis to understand driver perception. Verbal protocols provide a way to record the human thoughts while driving on road. However, real-time commentaries may remain incomplete in high-density traffic environments (Portouli et al., 2019). In addition, this method requires trained participants as it increases the cognitive workload on drivers (Grahn et al., 2020). If the participants are not trained, the cognitive workload might affect their driving tasks and road safety.

Questionnaire and interview methods are not likely to affect participant safety during the study. These methods are implemented to investigate driver perception and decision-making during communicative interactions (Kitazaki & Myhre, 2015; Strömberg et al., 2018). These interactions are introduced either through scenario description, sketch or simulated videos (Imbsweiler et al., 2018; Kitazaki & Myhre, 2015; Stoll et al., 2018; Stoll et al., 2019). However, the results of these studies suffer from low fidelity compared to others. For instance, Stoll et al. (2019) explained that participants overestimate the use of explicit signals in a survey than observational study. The results might require validation through driver behavior from an observational or field study (Imbsweiler et al., 2018).

Driving simulator is a safe and feasible alternative to measure driver perception and behavior (Mullen et al., 2011). According to Kaptein et al. (1996), driving simulator enables to study the impact of non-existent road elements on driver behavior with high fidelity. Previous research concluded that driving simulators provide accurate observations on driver decisions and behavior, which is based on the context (Alicandri, 1994; Desmond & Matthews, 1997; Fraser et al., 1994; Kaptein et al., 1996; Lee, 2003; Meuleners & Fraser, 2015). In the context of communicative interactions, some studies implemented driving simulator to study preferred cooperation behavior and effects of signals on driver perception (Ba et al., 2015; Kauffmann et al., 2018; Stoll et al., 2020). In these studies, drivers are asked to watch scenario videos on the driving simulator displays. Participants are then asked to fill relevant questionnaires to study driver perception and choices in communicative interactions. However, these studies did not study driver behavior in communicative interactions. Rettenmaier et al. (2020) filled this gap. The authors studied the passing behavior of HDV on narrow roads when interacting with eHMI equipped AVs. Further studies should investigate driver perception and behavior in communicative interactions with AVs in different driving contexts, using a driving simulator.

2.1.2 Vehicle signals

Vehicle signals act as the major source for an on-road communication between drivers (Ba et al., 2015). From the literature,

Table 2 provides a summary of vehicle signals in driver-driver communicative interactions. The signals convey driver intent (Renge, 2000). Ba et al. (2015) illustrated that vehicle signals have an effect on drivers' emotions, attitude, visual attention, and perception of others' behavior. Kitazaki & Myhre (2015) investigated that these signals affect driver's yielding decisions and confidence at an intersection. The interpretation of these signals, however, differs with the context (Ba et al., 2015; Björklund & Åberg, 2005; Moore et al., 2019; Renge, 2000). In addition, diversity in the signals is likely to affect driver perception and decisions (Kitazaki & Myhre, 2015; Uttley et al., 2020); which ultimately influences driving behavior and traffic safety (Ba et al., 2015; Ceunynck et al., 2013). These studies imply that vehicle signals have a relationship with traffic safety and efficiency.

Table 2: Summary on vehicle signals for driver-diver communicative interactions

Driving context	Maneuver type	Speed	Vehicle signal		
			Implicit signal	Explicit signal	Combined signal
T-intersection	Straight	Low	Acceleration, deceleration, stop, maintaining speed	Headlight flash, direction indicator, hand gesture, horn	NA
	Left	Low	Acceleration, deceleration, stop, maintaining speed	Headlight flash, direction indicator, hand gesture, horn, head movements	Turn indicator + edging, turn indicator + edging + headlight flash, turn indicator + gesture, turn indicator + gesture + advancing, stop + gesture, stop + headlight flash, stop + horn, decelerate + gesture, decelerate + headlight flash
	Right	Low	Acceleration, deceleration, stop	Turn indicator, hand gesture, head movements, headlight flash	Turn indicator + advancing, decelerate + gesture, decelerate + headlight flash + gesture, stop + gesture
X-intersection	Straight, Left, right	Low	Acceleration, maintain speed, deceleration, stop	Headlight flash, hand gesture	NA
Narrow road	Straight	Low	Acceleration, deceleration, maintaining speed, stop	Headlight flash, direction indicator, hand gesture, horn	NA
Shared space	Car-parking	Low	Maintaining speed, deceleration, stop	Indicator (turn and reverse), headlight flash, hand movements, head movements, looking towards another driver	NA
Highway	Lane change, merging	High	Acceleration, deceleration, maintaining speed	Indicator, indicator + arrow on the AR display, hazard lights	NA

Ceunynck et al. (2013) and Moore et al. (2019) classified vehicle signals from human driver into implicit and explicit signals. Implicit signals include vehicle driving styles such as yielding and non-yielding; whereas, explicit signals include horn, indicator lights, and driver-based signals such as eye-contact, hand and head gestures. Both of the signal types are relevant for communicative interactions to improve traffic safety (Dietrich, 2018).

Certain studies illustrate that human drivers prefer implicit over explicit signals in communicative interactions with other drivers (Dietrich, 2018; Imbsweiler et al., 2018; Portouli et al., 2019; Risto et al., 2017; Uttley et al., 2020). Drivers use implicit signals to establish a common meaning with other drivers (Risto et al., 2017). For instance, acceleration without vehicle indicator trigged other drivers to yield at an intersection (Portouli et al., 2019). In addition, Risto et al. (2017) illustrated that a slow moving car at an intersection indicates yielding and accelerating indicates that the driver will take the right of way. Most of the drivers rarely use explicit signals (Lee et al., 2020; Moore et al., 2019; Portouli et al., 2019). Moore et al. (2019) explained that the absence of explicit signals does not have a major impact on the safety of interactions with other road users.

On the other hand, some authors explain that explicit signals are likely to affect driver perception of other's cooperation in the interactions (Imbsweiler et al., 2018; Kauffmann et al., 2018; Portouli et al., 2019; Stoll et al., 2020, 2018; Uttley et al., 2020). Interpretation of explicit signals might differ with context and culture. According to Imbsweiler et al. (2018), explicit signals convey the defensive action of drivers. However, other authors explain that some drivers use explicit signals to make others yield (Portouliet al., 2019; Uttley et al., 2020). Another observation is that the explicit signals are likely to influence driver decisions to change speed and lane (Stoll et al., 2020, 2018). In a study by Stoll et al. (2018), indicator signal with arrow (i.e., direction of turn) has the largest effect on cooperation behavior. These observations imply that explicit signals influence driver decisions in the interactions. However, these studies did not study the effect of AV signals on driving behavior in communicative interactions.

Some studies suggest that drivers use explicit signals to resolve deadlock situations and negotiations (e.g., Dietrich, 2018; Kitazaki & Myhre, 2015; Portouli et al., 2019). Alongside implicit signals, driver-based explicit signals are likely to convey clear intent of driver in low-speed interactions (Dietrich, 2018; Imbsweiler et al., 2018; Uttley et al., 2020). However, driver-based explicit signals are unlikely to occur in higher levels of AVs due to the shift in user role (i.e., driver to passenger). The literature on human driver interactions suggested considering eHMI with implicit signals to improve traffic safety and efficiency (Dietrich, 2018; Imbsweiler et al., 2018; Kitazaki & Myhre, 2015; Möller et al., 2016; Portouli et al., 2019).

2.2 Automated vehicles

According to the Society of Automotive Engineers (SAE; 2018), AVs are classified into 6 levels of automation based on the system capabilities such as execution of dynamic driving tasks (lateral and longitudinal control, object and event detection and response, and fallback) and operational design domain (ODD; limited to certain road environment, type of behavior and state of the vehicle). Based on its capability, AV functionality differs with the levels of automation. Accordingly, the human user needs to take over the driving task. As the user role differs, communicative interactions between AVs and other road users are likely to vary.

The user is responsible as a driver for AVs with Level 1, 2 and 3 automated systems (SAE, 2018). The user, in Level 4 and 5, acts as a passenger in driverless AVs (SAE, 2018). When the automation is in control, users are unlikely to use the driving seat. This implies that the human driver is absent. Road users cannot use eye-contact or other forms of human-based informal signals in communication with driverless vehicles. Driverless vehicles, referred as AVs henceforth, build a 'social interaction void' (Rasouli et al., 2018). Rothenbucher et al. (2016) study showed that pedestrians are uncertain about the driverless car behavior in interactions. A probable explanation is that vehicle signals of driverless cars are different to conventional vehicle signals.

A possible solution is to use the concept of eHMI to convey the intent of AVs. This section explains the concept of eHMIs briefly, and then discusses the application of eHMIs in interaction with different human road users from the literature.

2.2.1 External human machine interfaces

Peng (2016) and Vinkhuyzen & Cefkin (2016) coined the term external human machine interface in 2016 (Winter & Dodou, 2021). eHMIs aim to reduce the communication void with other road users through "human-like" features to AVs (Peng, 2016; Vinkhuyzen & Cefkin, 2016). The interfaces offer a possibility to replace eye-contact and gestures in communication with human road users. eHMIs, however, are not just limited to adding "human-like" features to AVs. Schieben et al. (2019) suggested that eHMIs could serve as a multi-purpose tool in the interactions. For instance, eHMIs could convey information on AV intent, driving mode, perception of the environment, and cooperation capabilities. On similar lines, Winter & Dodou (2021) supported eHMIs through 4 arguments:

1. eHMIs could provide superhuman performance to human road users

2. Participants value AVs with eHMI than without eHMI

3. eHMI could provide more information than just AV intent

4. Implicit signals have limitations

eHMIs could potentially improve communicative interactions and enhance traffic safety, and efficiency in the mixed traffic environment.

2.2.2 Communicative interactions with pedestrians

Many studies (see Figure 7) explored communicative interactions between AVs and pedestrians (e.g., Bazilinskyy et al., 2020; Böckle et al., 2017; Cefkin et al., 2019). Farber (2016) and Lee et al. (2020) explained that a prerequisite for AVs is to use vehicle signals, that effectively communicate with road users. If not, traffic safety and efficiency are reduced in a mixed traffic environment (Lee et al., 2020). A possible solution is to understand the effect of different signals that road users use when interacting in traffic and suggest the relevant signals (e.g. Farber, 2016; Kitazaki & Myhre, 2015; Lee et al., 2020).

The literature is divided on suggesting the vehicle signals for pedestrian interactions. Few studies emphasize that pedestrians prefer to use implicit signals over explicit signals in communicative interactions with other drivers (e.g. Dey & Terken, 2017; Lee et al., 2020; Moore et al., 2019). Moore et al. (2019) utilized Wizard of Oz and Ghostdriver car methods to illustrate that the implicit signals, by itself, is a powerful eHMI during an interaction with pedestrians. Here, the Ghostdriver car did not use driver cues or eHMI to interact with the pedestrians.

On the other hand, most researchers suggest that AV requires an explicit eHMI to compensate for driver's inability to communicate with pedestrians (Habibovic et al., 2019; Lagström & Lundgren, 2016; Li et al., 2018; Matthews et al., 2018; Mirnig et al., 2017). These studies illustrate that an eHMI, alongside implicit signals, improves perceived safety, comfort and reaction time of pedestrians while crossing an AV. Habibovic et al. (2019) explained that eHMI is vital in negotiations as eHMI reduces ambiguity. This implies that the combined vehicle signals (i.e., implicit signals and eHMI) of an AV have a significant and positive effect on pedestrian interactions in negation situations. An explanation is that eHMI has the capability to support human road users in interpreting future AV behavior. These observations are rarely explored in communicative interactions between AVs and HDVs.

Dey et al. (2020) discussed various locations for the placement of eHMI to convey AV intent (see Figure 8). An eHMI could be mounted on the vehicle (e.g., roof, body grills); projected on the road as a message (e.g., symbols, trajectories, intention); placed on the infrastructure (e.g., smart roads, traffic lights) and attached to the pedestrians (e.g., smart watch, phone, tablet).

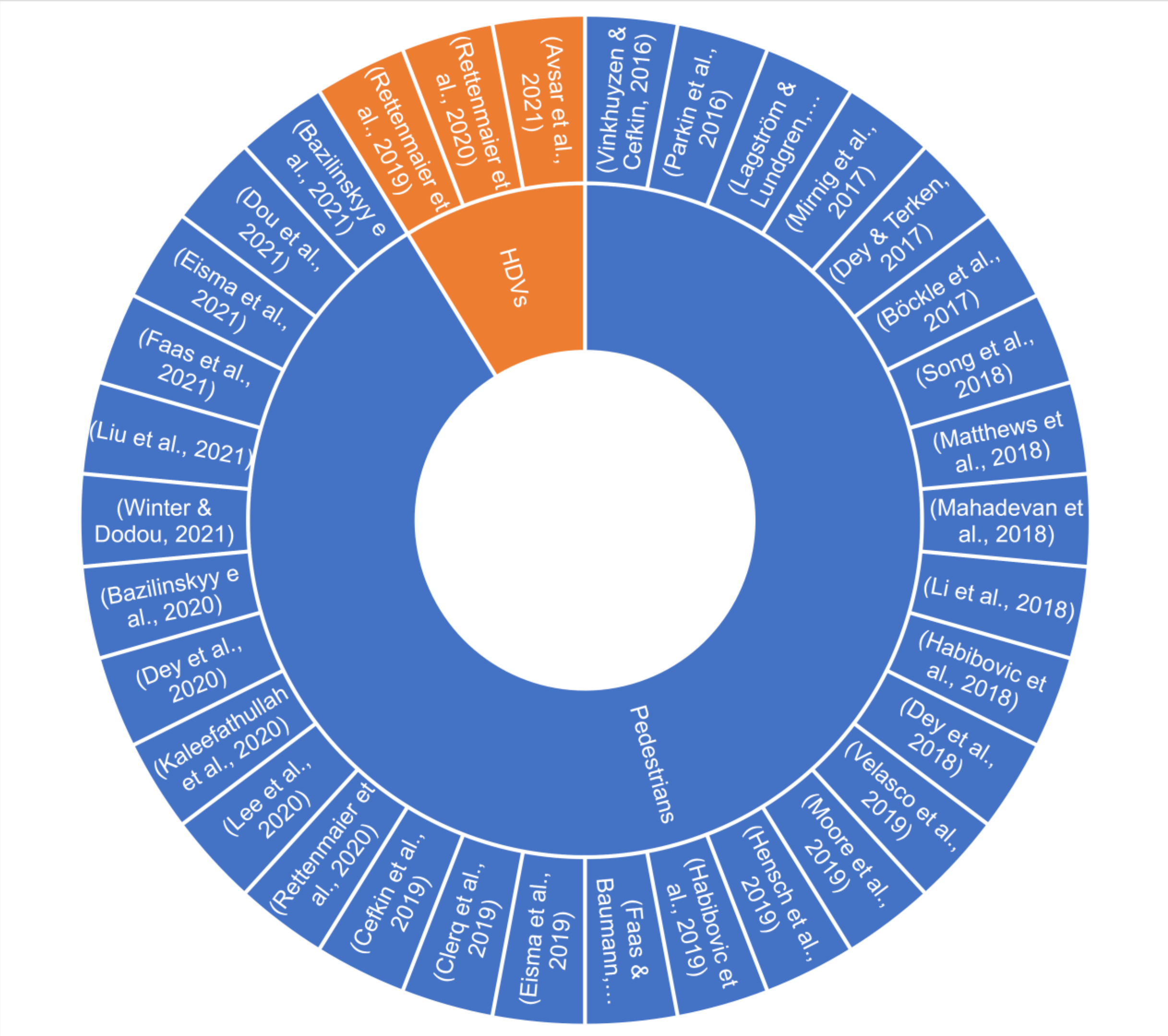


Figure 7: Studies on AVs' communicative interaction with pedestrians and human driven vehicles (HDVs).

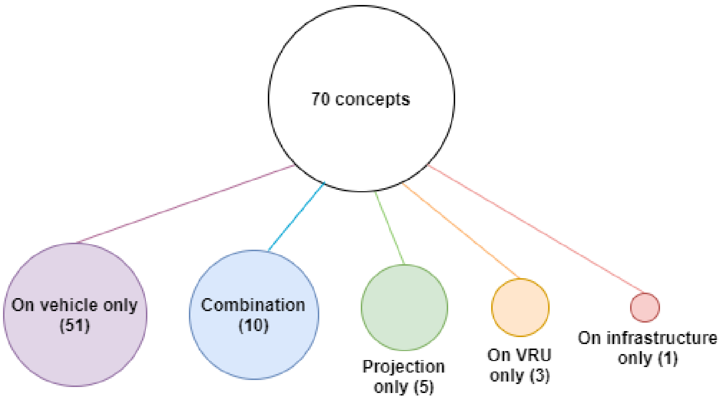


Figure 8: Placement of eHMI concepts differed in various studies (Dey et al., 2020). Most of the previous research studied eHMI concepts on vehicle. Least focus was given to eHMI concept on infrastructure.

Literature studied the impact of eHMI placement on pedestrians (e.g., Böckle et al., 2017; Dey et al., 2018; Mahadevan et al., 2018). Most of the studies focused on placing an eHMI on the vehicle (e.g., Böckle et al., 2017; Faas & Baumann, 2019; Habibovic et al., 2019). However, there is limited research on eHMI placement on the road infrastructure (Mahadevan et al., 2018). A possible explanation is that eHMI on infrastructure on street require high investments than eHMI on vehicle.

Mahadevan et al. (2018) illustrates that the pedestrians prefer eHMI on the street infrastructure besides eHMI on the vehicle. Infrastructure eHMI provides higher resolution and scalability of communication than eHMI on vehicle (Dey et al., 2020). Resolution of an eHMI conveys the clarity on which road user is the message intended, whereas scalability refers to the number of road users using an eHMI. Higher resolution and scalability improves communicative interactions between pedestrians and AVs (Dey et al., 2020). These observations are not yet studied for interactions between AVs and HDVs. Resolution and scalability play a vital role in communicative interactions with human drivers. For instance, eHMI on vehicle might offer poor resolution than eHMI on infrastructure at X-intersections. However, the challenge lies in assigning the signal to a specific vehicle. There is a need for to study the effect of eHMI placement on AV interactions with HDVs.

2.3 Communicative interactions with HDVs

Limited research (see Figure 7) explored communicative interactions between AVs and HDVs in the mixed traffic environment (Avsar et al., 2021; Rettenmaier et al., 2020). Rettenmaier et al. (2020) and Avsar et al. (2021) studied the effect of eHMI on the passing behavior of human driver on narrow roads, and gap-acceptance behavior at the intersections, respectively. Results of the studies show that eHMI improves human driver performance in a communicative interaction with AVs. However, all these studies used unidirectional eHMIs which are less relevant on roads, where multiple interactions occur in the mixed traffic environment. The studies focused on driver behavior, one of the two concepts of communicative interaction, but not on driver perception. In addition, the effect of eHMI placement on human driver performance is not studied. eHMI placement affects the resolution and scalability of communication in the interactions (Dey et al., 2020). Hence, there is a need to explore the effect of eHMI placement and form on communicative interactions with human drivers.

2.4 Measuring communicative interactions

Wilde (1976) studied communicative interactions between drivers with two crucial concepts: perception and communication of intent. In most of the communicative interactions, drivers communicate their intent through their driving behavior (Imbsweiler et al., 2018). Parasuraman et al. (2000) explains a relationship between driver perception and behavior. Previous research measured driver perception and behavior to understand communicative interactions between human drivers (e.g., Dietrich, 2018; Portouli et al., 2019; Stoll et al., 2019). Considering this, the following sub-sections focus on driver perception and driver behavior.

2.4.1 Driver perception

Human perception involves recognizing environmental elements and making judgements (Broadbent, 1958; Endsley, 1995; Steinfeld et al., 2006). Ram & Chand, (2016) explained that human perception of driving tasks (i.e., driver perception) influences the safety of traffic interactions. An explanation is that driver perception influences driving decisions and actions, thereby affecting the safety in interactions (Parasuraman et al., 2000). Literature widely studied driver perception on vehicle signals of HDVs in lane-change and unsignalized intersection scenarios (Imbsweiler et al., 2018; Kauffmann et al., 2018;

Kitazaki & Myhre, 2015; Portouli et al., 2019; Stoll et al., 2020). There are, however, limited studies that investigate driver perception on AV signal types (i.e., implicit signals and eHMIs) at unsignalized intersections.

Previous research analysed driver perception through qualitative methods such as verbal protocol analysis (Dietrich, 2018; Portouli et al., 2019). Interpretation of qualitative methods require higher inter-reliability and help from other researchers. On the other hand, semantic differential scale measures driver perception quantitatively (Zimmermann & Wettach, 2017). Takahashi & Kuroda (1996) explained that semantic differential scale (SDS) is easier and useful to measure human perception of robots in multiple dimensions such as experience and usability. A widely applied SDS to understand driver experience of an interaction is perceived criticality (Kauffmann et al., 2018; Neukum, 2003). Avsar et al. (2021) observed that eHMIs reduce perceived criticality of interactions with AVs. Emotions, another SDS, helps to understand human intention and perception in human-robot interactions (Fiore et al., 2013). Lundgren et al. (2017) and Zoellick et al. (2019) explained that emotions have a relationship with driver attitudes and behavior in the communicative interactions on road. However, emotions and perceived criticality are unlikely to reflect the workload experienced by the driver in communicative interactions. Perceived workload measures the discomfort level of drivers in the interactions. Some studies suggest a relationship between AV interactions and the perceived workload of driver (Eriksson et al., 2019; Heikoop et al., 2019; Stapel et al., 2019). As an eHMI provides AV intent, the information is likely to reduce the perceived workload of road user. However, perceived workload is rarely studied in human driver interactions with eHMI equipped AVs.

Driver perception is likely to have a relationship with human factor variables, such as trust and user acceptance (Zoellick et al., 2019). Trust plays a vital role in human-automation interactions (Lee & See, 2004). For instance, Zhang et al. (2019) illustrates that trust has a positive and significant effect on human adoption and acceptance of AVs.

eHMIs are likely to improve the social acceptance of AVs (Vinkhuyzen & Cefkin, 2016). Social acceptance could be measured through user acceptance and preferences (e.g., Beggiato & Krems, 2013; Hecht et al., 2020; Heesen et al., 2014). Zoellick et al. (2019) used user acceptance to measure the usability of AV technology in the communicative interactions with pedestrians. In these communicative interactions, Zoellick et al. (2019) observed that behavioral intention is influenced by perceived criticality, emotions, trust, and user acceptance of participants. This finding implies that the above perception variables, including human factors, are likely to affect road user preferences of AVs in the interactions. However, the perception variables are rarely explored to study the interactions between human drivers and AVs with eHMIs.

2.4.2 Driver behavior

Human driving behavior is complex and unpredictable. Previous research investigated driver behavior models for developing AVs, and relieve driver stress, reduce uncertainty, improve traffic safety and efficiency (Pathivada & Perumal, 2017; Riaz et al., 2018; Salvucci, 2006; Talebpour et al., 2016; Wang et al., 2014). These models make an effort to develop human-like AVs by adapting vehicle behavior to human driver behavior (Basu et al., 2017). Human-like AVs aim to reduce human error and improve social acceptance. One of the many challenges for human-like AVs is to execute communicative interactions with human drivers. Preliminary research developed decision-making algorithms to make the AVs more sociable, and safe (Möller et al., 2016; Riaz & Niazi, 2017; Schwarting et al., 2019). These models, however, assumed and simplified driver behavior. Very few studies explored driver behavior in communicative interactions (Dietrich, 2018). These interactions are generally observed at unsignalized T-intersections (Dietrich, 2018; Portouli et al., 2014; Risto et al., 2017). However, there are limited studies that examine driver behavior in communicative interactions at unsignalized T-intersections.

Driver behavior at unsignalized intersections (i.e., crossing behavior) determines the capacity and movement of vehicles at these intersections (Vinchurkar et al., 2020). Crossing behavior was measured using approaching speed and minimum speed (Choudhary & Velaga, 2019; Li et al., 2020), maximum acceleration and deceleration (Choudhary & Velaga, 2019; Li et al., 2020; Pawar & Patil, 2018), time to maximum braking, crossing decision, post encroachment time (Killi & Vedagiri, 2014; Li et al., 2020) and crossing time (Devarasetty et al., 2012; Li et al., 2020). These measures were selected by studies focusing on modeling driver behavior and predicting driver intent at unsignalized intersections.

3 Research need and questions

This section discusses research gaps in the literature and establishes the research need, and objective. Further, the main research question and sub-questions are explained. Finally, the hypotheses are mentioned.

3.1 Research need and objective

Automated vehicles interact with HDVs in a mixed traffic environment. These interactions, however, could be different than HDV-HDV interactions. The lack of human control or in some cases the human presence in AVs result in a social gap. This gap increases the difficulty for a human driver to clearly understand the vehicle signals of an AV (Rasouli et al., 2018). Improper communication with human drivers could lead to an increase in travel delays and road crashes, which ultimately reduces the social acceptance of AVs. Previous literature on driver-driver (Dietrich, 2018; Imbsweiler et al., 2018; Kitazaki & Myhre, 2015; Möller et al., 2016; Portouli et al., 2019), pedestrian-driver (Dietrich, 2018; Kitazaki & Myhre, 2015; Uttley et al., 2020) and pedestrian-AV (Habibovic et al., 2019; Li et al., 2018; Lundgren et al., 2017; Matthews et al., 2018; Mirnig et al., 2017; Vinkhuyzen & Cefkin, 2016) interactions suggest the application of eHMI, in addition to implicit signals, for AVs in mixed traffic environment. The purpose is to enhance AVs' social acceptance and reduce uncertainty in communicative interactions with human road users. Such suggestions, however, are questionable as the studies did not explicitly investigate the effect of eHMI in AV-HDV interactions. The question arises whether eHMIs are likely to improve communicative interactions. However, limited studies exist. In addition, AV interactions with road users are affected with the placement of eHMI on vehicle or infrastructure (Mahadevan et al., 2018). The placement of eHMI rises the question of "who" is responsible to develop and maintain the eHMI. For instance, whether road authority or AV manufacturer is responsible for constructing and maintaining the eHMI? Existing research did not make efforts to answer the question. Hence, there is a need to investigate the effect of eHMI placement on AV-HDV interactions.

On road studies suffer from low experimental control. On the other hand, qualitative methods (e.g., online questionnaire and survey) produce results that are different from reality (Imbsweiler et al., 2018; Stoll et al., 2019). Hence, there is a need to study AV-HDV interactions with a research method (e.g., driving simulator) that has optimal validity and experimental control.

In order to address these aspects, the main objective of this research is to study the effect of eHMIs in communicative interactions between HDV and AVs. This provides an understanding on whether eHMIs could improve traffic safety and interaction efficiency for AVs in a mixed traffic environment.

3.2 Conceptual framework

The conceptual framework of this research is exhibited in Figure 9 and is developed using the literature findings and the research objective. This framework explains communicative interactions between human drivers and interacting vehicles (i.e., HDV and AV), that are based on AV driving styles (i.e., yielding and non-yielding) and explicit signals (i.e., eHMI on vehicle and eHMI on infrastructure).

AVs could use eHMIs to convey intent with HDVs in the communicative interactions. Such interactions differ with *human driver characteristics, driver presence, road infrastructure, driving style*, and the existence and type of *eHMI* of AVs. *Driver presence* in vehicles

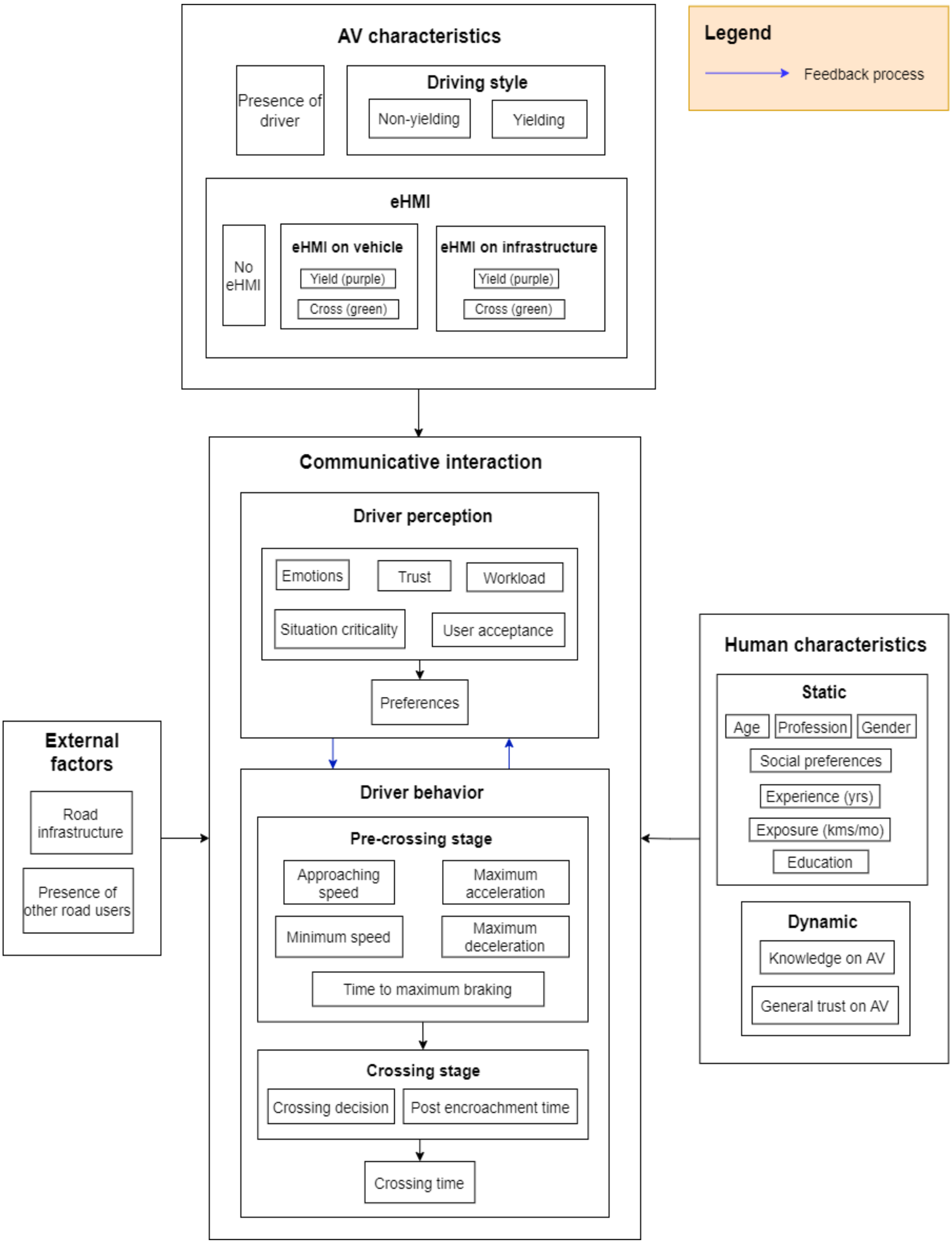


Figure 9: Conceptual framework of communicative interactions between human drivers and AVs.

influences other driver expectancy on the type of vehicle signals. For instance, human driver expects and uses human-based signals such as eye-contact, if they see a driver in the other vehicle. While interacting with an AV, a human driver understands the AV intention through *driving style* and *eHMIs*. AV *driving style*, in terms of vehicle movements, convey information on the future trajectory of the vehicle. eHMIs inform the human driver about AV intent. Green display requests human drivers to cross first, and purple advises human drivers to yield. eHMIs differ in the placement, either on vehicle or infrastructure.

AV *driving style* and *eHMIs* affect communicative interactions, in terms of perception and behavior, with human drivers. If the information of AV signals does not meet driver expectations, then they might experience the situation as critical and AVs as unsafe. Accordingly, drivers behave differently than expected.

Human driver characteristics affect their communicative interactions with AVs. Personal characteristics such as age, gender, profession, driving experience and social preferences affect drivers' understanding and their interactions with HDVs and AVs. Social preference of drivers influences their driving behavior. For instance, altruistic drivers give priority to other vehicles and take more time to maneuver. In addition, driver trust and knowledge of AV influence their judgement and interaction with AVs.

In addition, *external factors* such as road infrastructure and presence of other road users influence communicative interactions between vehicles. Road infrastructure, such as an intersection, offers conflict space that is shared by human and automated driven vehicles. The road users negotiate their right-of-way through communication in the conflict space; which determines driver behavior in the interactions (Wilde, 1976). For instance, a driver cooperates and decelerates to provide right-of-way to other vehicles at an intersection. Similarly, the presence of other road users affects driver behavior (Uttley et al., 2020). An example, a vehicle stops to let the pedestrians cross.

Human drivers study the intent of other vehicles using their signals (i.e., driving styles and eHMIs) in communicative interactions. *Driver perception* of others' intent is reflected in their judgement of situation criticality, emotions, perceived workload, trust and acceptance of AV based on its signals. The above perception variables also influence driver preferences. Furthermore, drivers' perception of a situation influences their actions (e.g., crossing behavior). These actions differ with the type of driver maneuver and conflict space on road. While crossing at unsignalized T-intersections, drivers communicate their intent through *driving behavior* at three stages, namely pre-crossing, crossing, and post-crossing stages. Pre-crossing stage includes driver behavior variables such as approaching speed, maximum acceleration, maximum deceleration, minimum speed, and time to maximum braking. Crossing stage includes crossing decision and post encroachment time. Post-crossing stage includes crossing time. Observations at different stages give a deeper insight into the effect of eHMIs on driver behavior. Driver behavior is influenced by their perception of AV in the interaction (Parasuraman et al., 2000). If a driver sees the eHMI and perceives the AV as non-yielding then the driver waits and takes more time to cross. On the other hand, *driver behavior* and experience with an AV influences perception, such as trust and acceptance of an AV. For instance, if a driver faces a safety issue during a communicative interaction with an AV, then the driver develops a low trust and acceptance score for AV signal. Hence, the relation between driver perception and behavior is cyclic.

3.3 Research questions

Following the identified research gaps, the main research question of this study is:

What is the effect of eHMIs on AVs' communicative interaction with human drivers who perform a right-turn maneuver at unsignalized T-intersections?

To answer it, five sub-questions are developed:

1. What are the effects of eHMI on driver perception?
2. What are the effects of eHMI on driver behavior with respect to AV driving style?
3. Which factors related to eHMI conditions, driver characteristics and perception influence driver preference for AVs?
4. Which of the AV and driver characteristics, perception, and pre-crossing behavior variables influence the critical events during right turn maneuver?

5. What is the effect of AV characteristics, driver characteristics, perception, pre-crossing and crossing behavior on the time drivers take to complete right turn maneuver?

Sub-question 1 explores the relationship between the eHMI conditions and each of the perception variables. Perception variables, including situation criticality, emotions, trust, user acceptance, workload, and preferences, provide driver judgements of the AV interactions. First, the question focuses on whether an eHMI enhances driver perception in the interactions. Second, the question studies the effect of eHMI placement on driver comprehension.

Sub-question 2 examines the effect of eHMI presence and its placement on human driver behavior in the interactions. The relationship with human behavior is studied over AV driving style (i.e., non-yielding and yielding). Human driver behavior is observed across pre-crossing, crossing, and post-crossing stages. The question aids the researcher to understand the interaction patterns between human drivers and AVs. The driving behavior in the interactions could be used to understand the variation in traffic safety and efficiency of the HDV-AV interactions.

Sub-question 3 identifies the relevant factors, among the eHMI conditions, driver characteristics, and perception variables, that predict the driver preferences for AVs. The identified variables improve the social acceptance of AVs.

Sub-question 4 predicts the combined effect of AV characteristics (i.e., driving style and eHMI), driver characteristics (e.g., age, gender, education), perception (e.g., emotions, rust, user acceptance), and pre-crossing behavior (e.g., approaching speed, maximum deceleration, time to maximum braking). The predicted variable is the critical events from Post Encroachment Time (PET) in the crossing stage. The critical events (from PET) provide inference for traffic safety.

Sub-question 5 understands the combined effect of sub-question 4 variables, in addition to crossing behavior variables (i.e., crossing decision, and post encroachment time). The target variable for the prediction is crossing time from the post-crossing stage. The results contribute to understand the efficiency of AV-HDV interactions.

3.4 Hypothesis

In order to answer the research questions, various hypotheses are formulated and tested to understand the effect of eHMIs on driver perception and behavior. Literature findings are used to compose the following hypotheses:

1. eHMIs improve driver perception of AV in the interactions.
2. Driver compliance with AV instruction increases for the eHMI conditions and more specifically for the eHMI on infrastructure.
3. Drivers are likely to prefer AVs with eHMIs, where more preference is given to eHMI on vehicle.
4. eHMI on vehicle is likely to reduce critical events between HDVs and AVs than eHMI on infrastructure and baseline conditions.
5. eHMI on infrastructure is probable to decrease the crossing time of drivers than eHMI on vehicle and baseline conditions.

3.5 Research methodology framework

Figure 10 illustrates the stepwise approach of research methodology to achieve the objective.

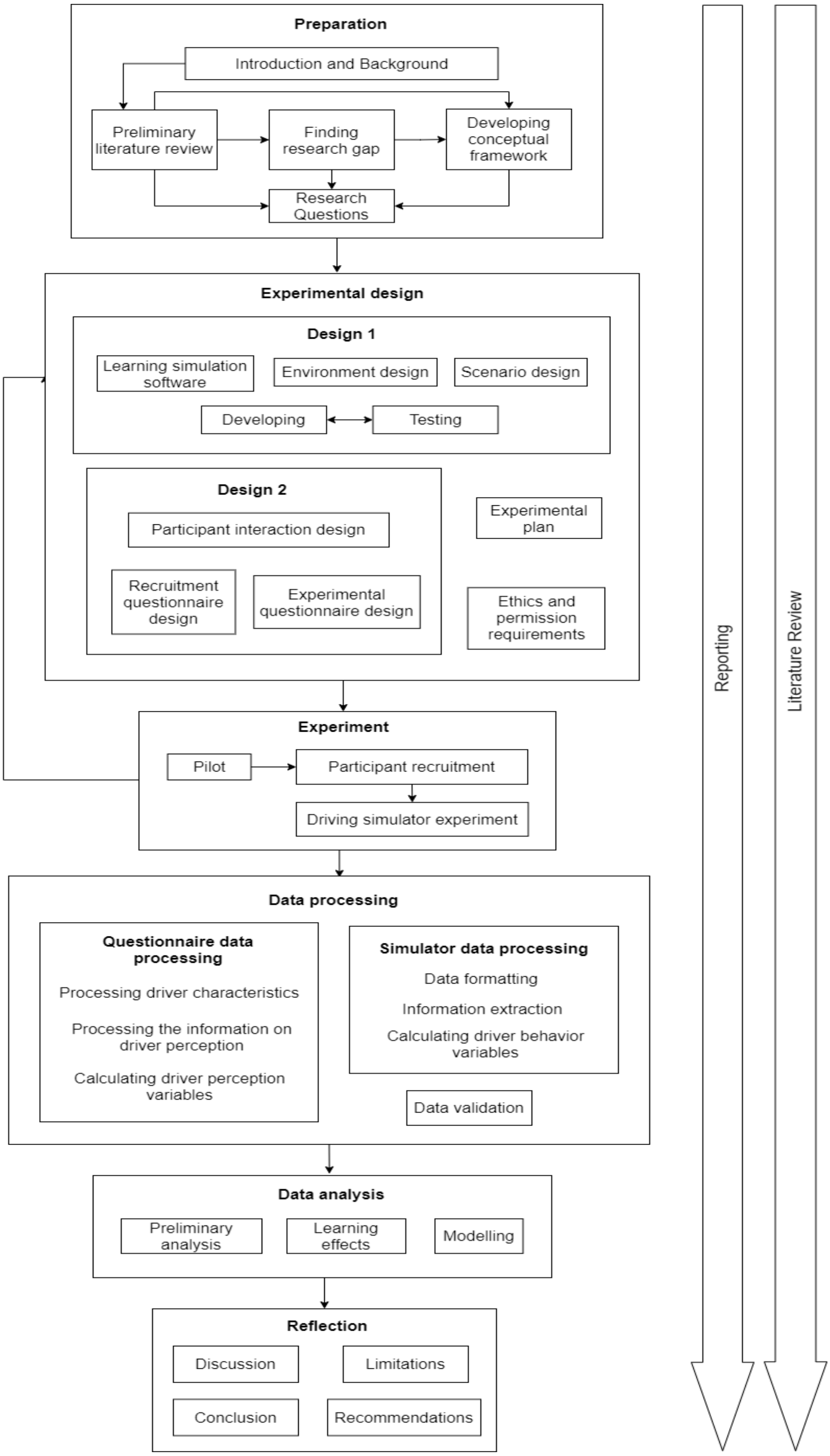


Figure 10: Research methodology framework.

4 Experiment

This section describes in detail the research methodology and experiment setup, including participant recruitment, apparatus, design, experimental procedure and lessons learnt from the pilot. This experiment involves variables that require a controlled environment to study communicative interactions between human drivers and AVs. A driving simulator, supported by an online survey, is used as the experimental method.

4.1 Participant recruitment

The eligibility criteria were that the participants have a driving license and at least a year of driving experience. Participants were recruited through an advertisement which was shared on social media, RHDHV employee groups, and a participant list from another driving simulator experiment[1] at the Department of Transport and Planning (T&P), TU Delft. Human Research Ethics Committee (HREC), TU Delft approved the experiment.

4.2 Apparatus

This research involved a two-phase experiment. First, participants answered a Qualtrics survey on demographics and social preferences through their own input devices. Second, participants drove in a fixed-base driving simulator (see Figure 11) located at the T&P department. The simulator had 3 ultra-HD (High-Definition) resolution screens with 180° field of view. The simulator was equipped with Fanatec steering wheel, brake and gas pedal. Pre-, mid- and post-experiment surveys were answered on a tablet.

Figure 11: Participant driving in a fixed-base simulator.

4.3 Design

Scenarios, experimental layout and questionnaires were designed to answer the research question in section 3.3. Scenarios and experimental layouts were designed with Unity 3D (version – 5.5f.2.1). Questionnaires were developed in Qualtrics.

4.3.1 Scenarios

The experiment consisted of 3 scenarios[2] that differ in the placement of eHMI for driverless AV (see Figure 12). Interaction with an AV, equipped with no eHMI, acted as the baseline

[1] Recruitment trick: Parallel to my thesis, I worked as a student assistant for a PhD's driving simulator experiment. I organised both the experiments in a cyclic process to recruit more participants despite COVID-19. In the first two weeks, I organised the PhD's experiment. I invited those participants for my experiment in the following weeks. Later, I invited the participants from my experiment to the PhD experiment, which resumed later.

[2] To view video scenarios, click here. The videos illustrate a participant driving in a simulator for 3 scenarios: baseline, eHMI on vehicle, and eHMI on infrastructure.

condition (Figure 13). The second condition included an eHMI on the roof of AV (Figure 14 and Figure 15); whereas, eHMI on infrastructure (Figure 16) represented the third condition.

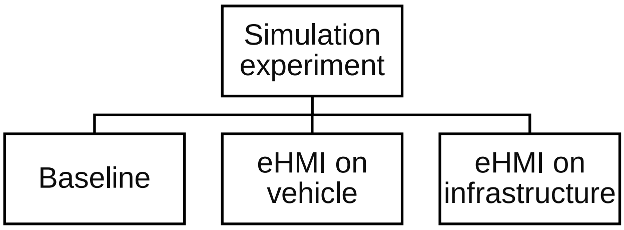


Figure 12: Scenarios for each participant in the simulator experiment.

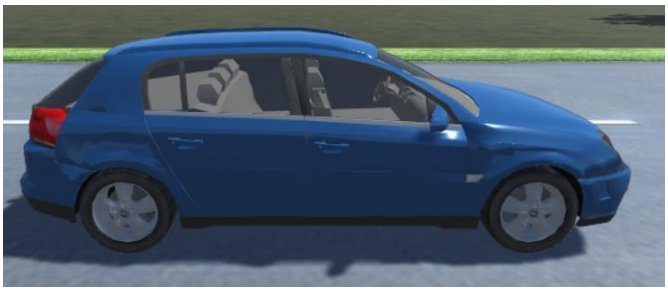


Figure 13: AV with no eHMI on the roof top.

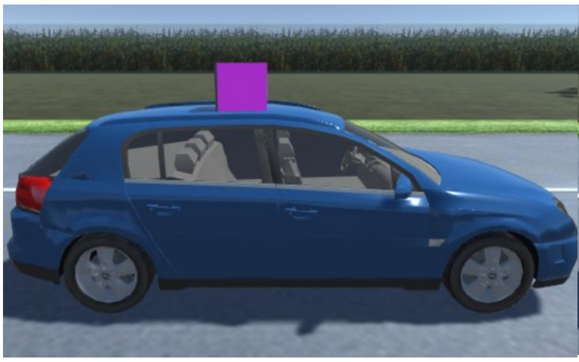


Figure 14: AV with an eHMI exhibiting purple to signal HDVs to yield.

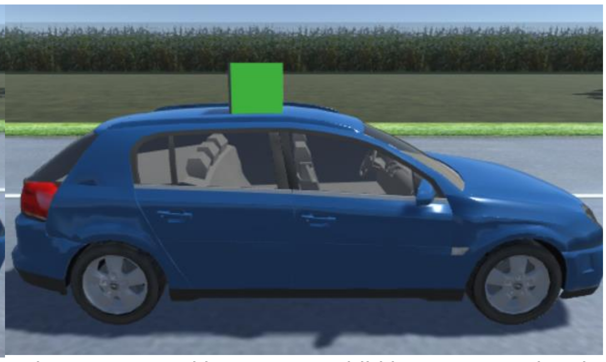
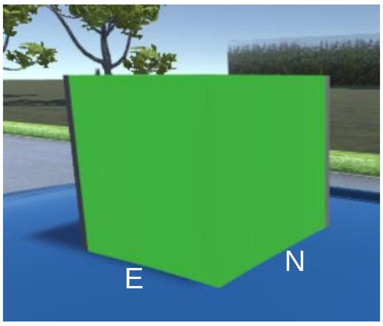


Figure 15: AV with an eHMI exhibiting green to signal HDVs to cross.

Figure 16: eHMI on the infrastructure where signals communicate AV intent. For instance, AV requests the HDV to cross first through a green signal.

eHMIs represented AV intention. In the first condition (i.e., baseline), AV conveyed its intent implicitly (i.e., yielding or non-yielding) but not explicitly. For the remaining two eHMI conditions, AV informed intent implicitly and explicitly. Explicit communication (i.e., eHMI) was in the form of light display rather than direction arrows, laser projection and text. These forms of communication are less likely to be visible from a farther distance (Hensch et al., 2019; Rettenmaier et al., 2019).

eHMI on vehicle, the second condition, exhibited AV intent in the form of a light displaying cube placed on the top of AV (see Figure 14 and Figure 15). Each cube's face, which represented the direction of information propagation, provided a better resolution of communication than unidirectional eHMIs. For instance, if the cube was illuminated along North and East faces (see the left picture in Figure 17) then the AV communicated its intent to vehicles in its North-East direction only.



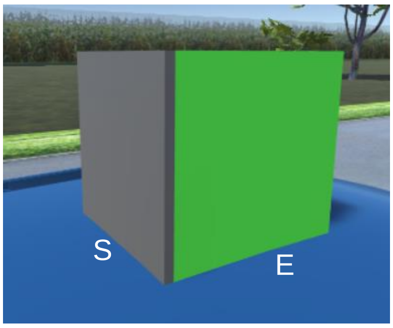


Figure 17: eHMI signalling AV intent in the form of colour display. Green display on North-East faces (left figure) signal the vehicles coming from North-East direction to cross at the intersection. Grey display on South face (right figure) indicates that eHMI is inactive in that direction.

The final condition, eHMI on infrastructure, conveyed AV intent through street infrastructure (see Figure 16, [Mahadevan et al., 2018]) in the form of light display; that was similar to eHMI on vehicle. eHMI on infrastructure was inspired by the concept of regular traffic signals. Two signals were placed at the intersection to make the identification of eHMI convenient for participants. eHMI on infrastructure updated the light display with the communication signal from AV.

AV displayed purple (see Figure 14) to signal 'yield' (i.e., please do NOT cross) and green (see Figure 15) to signal 'do not yield' (i.e., please cross; [Bazilinskyy et al., 2020]). Red and cyan were not used as the colors confuse other road users about AV intent (Bazilinskyy et al., 2020; Dey et al., 2020).

Participant vehicle (i.e., HDV) and AV interacted on a distributor road of speed limit 80 kmph. According to SWOV (2016) and Wegman & Aarts (2006), 50 kmph is the safe speed at a distributor road intersection with potential side impact between cars. In this experiment, an advisory speed limit sign of 50 kmph was placed 100 m away from the intersection. AV started at 50 kmph when it was visible to the participant. After its visibility, AV differed in driving style (i.e., non-yielding vs yielding). A non-yielding vehicle moves at 50 kmph throughout the intersection. On the other hand, the yielding vehicle decelerates with 3.0 m/s2. This was in line with a driving simulator study by Yan et al. (2008), who identified 3.0 m/s2 as the mean maximum deceleration rate at an intersection. The yielding AV decelerated from 50 kmph (at 50 m before the intersection) to 15 kmph (at 20 m before the intersection) in Figure 18. The braking distance and time were 30 m and 3.2 s. Once the AV reached 15 kmph near the intersection, it maintained the speed until the exit of the intersection.

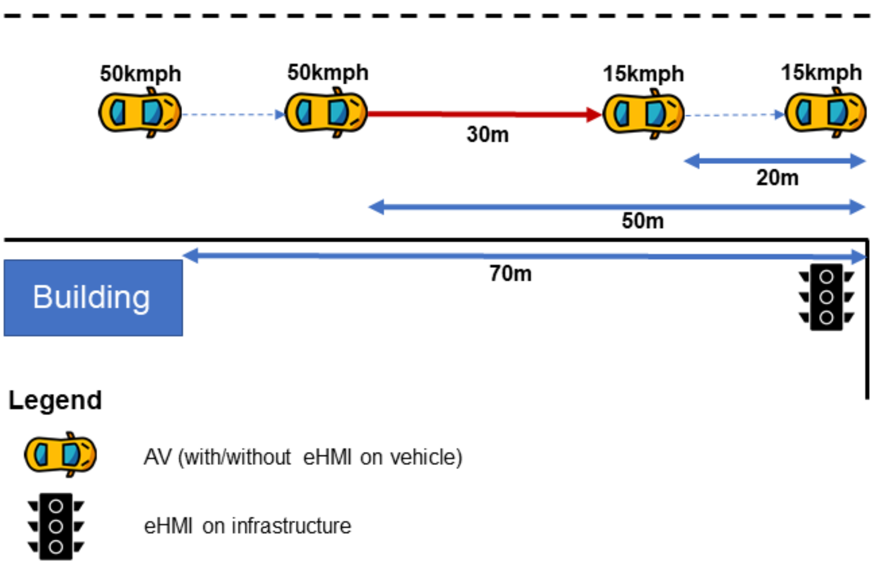


Figure 18: Yielding behavior of an AV which approaches the intersection at 50 kmph. AV starts to yield at 50 m from the intersection with 3.0 m/s2 (approximately). The braking distance is 30 m and the final speed of AV is 15 kmph.

4.3.2 Experimental layout

The experimental layout was designed in Unity 3D (version – 5.5.2f.1). In the experiment, HDV and AV interacted at unsignalized T-intersections (see Figure 19). Participants performed right turn maneuvers and interacted with AV on the left. AV movement and eHMIs were trigged when HDV reached 70 m, referred to as trigger distance, from the intersection. ASVV 2012 (CROW, 2012) recommended 70 m as the minimum clear sight distance for a distributor road of 50kmph advisory speed limit near the intersection. If the participant drove at 50 kmph (variation within +/- 10 kmph) and reached the trigger distance, AV was visible, and it started at same speed and 70 m from the intersection (c.f. Yang et al., 2019). HDV drivers identified the trigger location through a right-turning sign (see Figure 20). Another right-turning sign was placed at the intersection (10 m from the center) to remind the participants about the next maneuver to reach the destination.

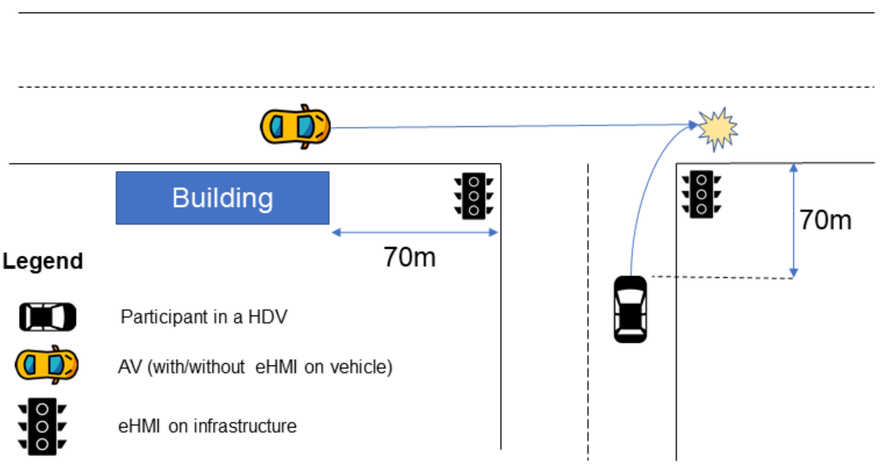


Figure 19: HDV and AV interact at unsignalized T-intersection. AV starts to move and exhibit eHMI signals when HDV reaches trigger location, placed at 70 m from the intersection.

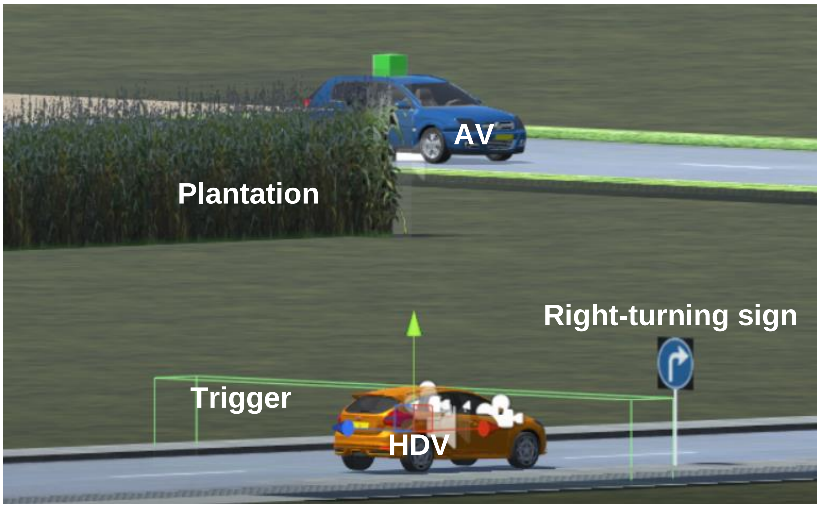


Figure 20: HDV drives at 50 kmph and reaches the trigger, which initiates the eHMI and AV on the other road. The trigger is identified by the driver with a right-turning sign, which was placed 70 m from the intersection. A plantation prevents the participant from noticing the immediate appearance of AV. The figure represents a scene view in Unity.

Every participant drove in an 8 km-road network for each scenario (see Figure 21). The network consisted of ten right-turns and four left-turn intersections to reduce monotony. In addition, some road sections of the network were designed longer (1500 m) than the others (400 m).

To make the experimental design more realistic, an obstruction in the form of a building or plantation (see Figure 20) existed along the roadside of AV and at 70 m from the intersection. The plantation prevented the participant from noticing the abrupt appearance of AV due to the trigger. In addition, randomized traffic was generated in the opposite lane of AV to introduce complexity in the interaction. Certain design aspects were made to improve the visibility of eHMI to the participant. For instance, the ground was colored dark-brown, the sun was set at 90 degrees to the ground, and a wheat plantation was placed opposite the intersection.

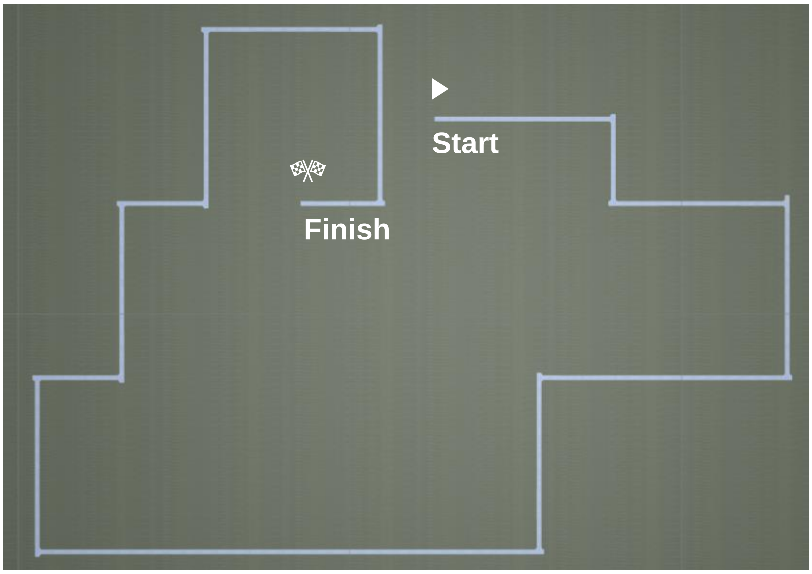


Figure 21: Road network for a scenario, where the participant interacts with AV at right-turn intersections. Participant starts at the start line and drives 8 kms before reaching the finish line.

4.3.3 Questionnaire

Questionnaire acts as a simple tool to capture information from the participants (McLeod, 2018). Participant information included social demographics, driving experiences and initial trust on AVs. This experiment implemented questionnaires (see Appendix B) at three stages:

a) Pre-experiment questionnaire

The initial step was to recruit participants based on eligibility and gain insights into their driver characteristics. A recruitment questionnaire (see Appendix B.1) was developed to collect driver characteristics, social preferences, general trust and knowledge on AVs. In addition, participants were provided with brief information on simulator experiment and regulations on data protection and COVID-19. Participants were then asked to fill the recruitment questions, consent form (see Appendix B.2) and read the instructions (see Appendix B.3).

b) Mid-experiment questionnaire

Sub-question 1 focused on comparing driver perception of AV between different scenarios. At the end of each scenario, participants filled an 8-minute-long questionnaire on their perceived criticality, trust, user acceptance, emotions and NASA-TLX workload. Appendix B.4 illustrated the questions, measured on an ordinal scale. The observations might depend on the visibility of AV and its eHMIs to the participant.

c) Post-experiment questionnaire

Finally, a post-experiment questionnaire (see Appendix B.5) was developed to understand the participants' decision-making, perceived changes in driving behavior and general trust in AVs and driving simulator experience. The driving simulator might induce discomfort in some candidates (Mourant & Thattacherry, 2000). Hence, they were asked to fill a simulator sickness questionnaire at the end of the experiment, which consisted 16 items to measure nausea, oculomotor disturbances and disorientation (Kennedy et al., 1993). Visual fidelity, involvement, realism and interface quality of driving simulator were observed through a 19-item presence questionnaire (Jerome & Singer, 2005).

4.4 Procedure

This experiment was conducted in two phases. In the first phase, the pre-experiment questionnaire was shared using social media platforms. On the first page of questionnaire, participants were provided with basic information on the research. They consented to participate in phase two, the driving simulator experiment. Participant information from both phases was required to answer the research questions.

Participants were requested to perform the driving simulator experiment. Initially, participants were briefed about the experiment and eHMIs of AV. eHMIs represented AVs' intent but not traffic rules. So, participants had the right to not comply with AV's intent. Before the actual experimental, they performed a test drive to become familiar with the vehicle and environment (Kauffmann et al., 2018). This was expected to reduce the effect of creating a learning curve while driving in the simulator. Once the participants felt confident in the test drive, they started the actual experiment. Participants were requested to reach the trigger distance with 50 kmph, observe the AV, follow the direction signs to the destination and repeat it for three scenarios. The order of scenarios was randomised among the participants to account for the learning effect. In each scenario, they performed ten right-turning maneuvers when merging with an AV approaching from their left-hand side (see Figure 22). Participants were requested to follow traffic rules and drive close to speed limits.

Further, participants were not informed whether AV (un)follows right-hand rule to reduce anxiety (Pawar & Patil, 2018). In each scenario, five AVs yield and the other five do not yield the right of way for the participant. The appearance order of the yielding and non-yielding AVs was randomised across the scenarios. After each scenario, participants were asked to answer a mid-experiment questionnaire. While the participants were filling the questionnaire, the researcher saved experimental data and loaded the following scenario. The total experimental duration was approximately 70 minutes.

Figure 22: Participant side view (left figure) and front view (right figure) of AV with eHMI on vehicle.

Participants were requested not to perform any secondary tasks while driving as this affects driver cognition and behavior (Stoll et al., 2020). If the participants felt unwell, they were requested to quit the experiment. On competition of driving task, participants were asked to fill a post-experiment questionnaire to measure their overall experience with the experiment. In addition, they were asked interview questions to understand their preference for AVs and suggestions. Finally, participants were debriefed (see Appendix B.6), thanked, and gifted a 10-euro bol.com voucher for participation.

4.5 Lessons from the pilot

Five pilot tests were conducted before the start of experiment. The main aim of these tests was to identify loopholes in the experimental and scenario design. These loopholes reduced the realistic experience of the experiment for the participants. In addition, the researcher identified practical challenges and practised communication with the participants.

The pilot tests were organised in two different batches. Feedback from the first batch of participants was implemented in the scenarios for the next batch. This technique aided in evaluating the lessons from the pilot. Pilot tests were conducted in the first week of June and July 2021. The main lessons learned were:

1. Some participants expressed that the steering wheel and brake pedal were too rigid to use. This problem affected the driver decision while performing a right turning maneuver. The researcher increased sensitivity and reduced rigidity of the steering wheel and brake pedal. Due to a firmware issue, the steering wheel did not have power steering. Hence, steering wheel data were not analysed.
2. A single eHMI on infrastructure reduced the convenience for pilot participants, as they needed to focus on multiple objects such as AV, eHMI and road to make a decision. Hence, participants expressed that they did not consider eHMI on infrastructure for decision-making. A solution was to place two eHMIs on either side of the road near the intersection, which increased the convenience for the second batch of participants.
3. Initially, the differences in eHMI conditions were not exhibited as figures in pre-briefing. Participants had difficulty in identifying it during the experiment. Alongside the purpose of eHMI, pictures were shown in the pre-briefing document.
4. Initially, the trigger distance was 30 m as suggested by Rettenmaier et al. (2020) for vehicular interactions on a 30 kmph speed limit road in a driving simulator. However,

three participants in our pilot study expressed 30 m as a short distance, which did not allow them to react, make a decision and perform a maneuver. A possible explanation was the difference in speed limits of both studies. Our experiment has an advisory speed limit of 50 kmph at the intersection. AVSS 2012 (CROW, 2012) suggested a clear sight distance of 70 m, which was tested to be sufficient for the participants to make a decision before they reach the intersection.

5. All the participants differentiated yielding from non-yielding vehicles when the AV decelerated at 3.0 m/s2 and 50 m from the intersection.
6. During the experiment, pen and paper-based questionnaires were adapted to an online format on a tablet to reduce data collection errors.

4.6 Analysis method

Experimental data was analysed to answer the research question. Analysis methods in this experiment included preliminary analysis and analytical modelling (Oskina, 2019). Preliminary analysis provided a basic understanding of significant interactions between the scenarios and measured variables. Preliminary analysis included descriptive and inferential statistics. Descriptive statistics were performed with bar charts, box-violin plots, and speed profiles in R program. The plots depicted possible trends in data across scenarios. Significance and inferences of the trends were studied through inferential statistics (Gonick & Smith, 1993). Garth (2008) provided steps to conduct inferential statistics in SPSS (version 26.0). Application of inferential statistics relied on analysis purpose, data format and parametricity (Oskina, 2019).

On the other hand, analytical model used mathematical analytic function to describe and predict changes in the measured variables (Mazur, 2006). Selection of model relied on the target variable and its parametricity, and hierarchical design (e.g., repeated measures) of the experiment (Dickey et al., 2010). In this research, target variables were non-parametric and the experiment followed a repeated measures design. Hence, a generalized linear mixed model (GLMM) was used (Dickey et al., 2010). GLMM expressed a linear relationship between the independent variables and target variables. Analysis method was further discussed in section 6.

5 Data processing

In the previous section, the experimental method and procedure were discussed. The driving simulator experiment was conducted for 3 weeks from July 5th, 2021. Experimental data was collected through questionnaires, interviews and driving simulator. The collected raw data, extraction of relevant variables and data cleaning procedure are explained in this section. Further an overview of processed data is provided. The data was later analysed to gain insights on the effect of AV's eHMI on human-driver interactions.

5.1 Description of raw data

Raw data collected from multiple questionnaires, interviews and driving simulator is discussed in this section.

5.1.1 Survey data

As discussed in section 4.3.3, survey data from interviews and multiple questionnaires were collected at different phases of the experiment. Questionnaires shared during the recruitment phase, mid-experiment, and after the experiment provide the required subjective information on participant perception and behavior. However, questionnaires in this experiment might not provide the reasoning behind the participant driving choices. Interview questions filled this gap. Table 3 provides a list of variables which are extracted from the questionnaire and interview data.

Table 3: Extracted variables from the questionnaire and interview data.

Pre-experiment	Mid-experiment (after every scenario)	Post-experiment	Interview
• Age • Gender • Education • Employment • Driving experience in years • Driving exposure in kilometres per year • Social preferences (SP) • General trust on AVs • Driver knowledge on AVs	• Perceived criticality • Trust • User acceptance • Emotions • NASA-TLX workload	• General trust on AVs • Virtual presence • Simulator sickness	• Self-reported effect of eHMI on their decision-making • Preference for AVs based on eHMIs • Experienced difference in AV driving style • Suggestions to improve communication systems of AVs

5.1.2 Behavior data

Behavior data were collected from the driving simulator after each scenario for a participant. Data, which was available in JSON format, contains 50 observations for every second of driving. Each observation recorded timestamp, velocity, acceleration, direction, and position coordinates of HDV and AVs. Timestamp (s) recorded the time-series when interactions between HDV and AVs occur. Velocity (m/s), heading (°), position (m) and acceleration (m/s^2) of HDV and AVs were measured along 3 dimensions (i.e., X, Y and Z).

5.2 Survey data pre-processing

This section explains the method to pre-process the questionnaire and interview data from section 5.1.1. Initially, the data was processed to remove personal information of participants. Responses from the pre-experiment questionnaire were synchronised with interviews, mid- and post-experiment questionnaires. Finally, survey data is described.

5.2.1 Initial processing

Personal information of the participants, such as name and email address, was removed from the synchronised dataset and anonymous IDs were assigned. All the questionnaire data was compiled into a CSV file format. Another file included participant comments. During the experiment, participants revealed relevant information that reduce errors in the collected data (see section 5.4.1).

Pre-experiment questionnaire on participant socio-demographics included Social Value Orientation (SVO) to understand social preferences (e.g., altruistic, prosocial, individualistic, and competitive) of participants. SVO was measured with a *slider measure*. The *slider measure* had 6 items (see Appendix B.1) on a continuous scale to evaluate social preferences (see Murphy et al. [2011] for procedure). The participant allocated resources for oneself and others' outcomes using the tool. Resource allocation determined the social preference of the participant.

5.2.2 Calculation of driver perception variables

This section explains the methods from the literature to calculate perception variables from the mid-experiment questionnaire for each scenario. The following variables were calculated:

- Perceived criticality: During AV-HDV interaction, Kauffmann et al. (2018) measured driver perception of criticality using a single-item question. The responses were measured on an ordinal scale of 1 to 10. Based on the responses, the situation was categorized as harmless (1 to 3), unpleasant (4 to 6), dangerous (7 to 9), or uncontrollable (10).
- Trust: Soni (2020) observed trust on an ordinal scale using a single-item question on AV-HDV interaction.
- User acceptance: Van Der Laan et al. (1997) measured user acceptance of AV technology in two dimensions: usefulness and satisfaction. These dimensions were measured using 9 questions on a scale of -2 to +2.
- Emotions: Bradley & Lang (1994) assessed emotions along three dimensions: pleasure, arousal and dominance. Pleasure expressed whether a participant was sad or happy in the scenario. Arousal measured the excitement and calmness levels of a participant; whereas dominance assessed the control level of participant in the scenario. These dimensions were measured on an ordinal scale ranging between 1 to 9.
- NASA-TLX workload: Hart & Staveland (1988) measured subjective workload on six dimensions: mental demand, physical demand, temporal demand, frustration, performance and effort. These dimensions were observed, on a scale of 1 to 20, using 6 questions. Later, the responses in each dimension were reduced to percentages and their mean is used to compute overall workload (Clercq et al., 2019).
- Preferences: During post-experiment, an interview question was asked to understand the participant preference for AVs based on eHMI conditions. Participants expressed their preference in terms of a rank for each condition. If an AV with eHMI on vehicle received rank 1 then the participant showed high

preference towards that AV. On the other hand, rank 2 represented medium preference and rank 3 represented least preference. Later, participants explained their reasons for preferred choices.

5.3 Behavior data pre-processing

During the experiment, data from each driving scenario was saved with an anonymous id. Each scenario file of a participant was converted from JSON format to CSV format. Conversion algorithm was developed in an open-source programme based on JSON, Jupyter Notebook. All the files were combined into a single CSV based on anonymous id and scenario. Combination algorithm was created in the R Program. The combined data file contained 132 rows and 21 columns. The file was used to calculate the driver behavior variables.

Driver behavior variables were extracted for each AV-HDV interaction per scenario per participant. The driving behavior was also differentiated for the AV driving style: non-yielding and yielding. Furthermore, the behavior variables were studied at different stages of crossing at the intersection (Li et al., 2020). The stages were pre-crossing, crossing and post-crossing. Pre-crossing stage occurred when the participant crossed the trigger location and was approaching the intersection. Next, participant made a crossing decision and executed the right-turn maneuver in the crossing stage. Finally, the participant exited the intersection in the post-crossing stage. A deeper understanding of driver behavior was made through observations at multiple-crossing stages. Table 4 defines the driver behavior

Table 4: Definition of driving behavior variables.

Driving stage	Behavior variable	Unit	Definition
Pre-crossing	Approaching speed	m/s	Average speed of HDV from the moment when AV was triggered to the moment when HDV reached the intersection.
	Minimum speed	m/s	Minimum speed of HDV before reaching the intersection but after AV was triggered.
	Maximum acceleration	m/s^2	Maximum acceleration of HDV before it reached the intersection.
	Maximum deceleration	m/s^2	Maximum deceleration of HDV before it reached the intersection.
	Time to maximum braking	s	Time from the moment when AV was triggered to the moment when HDV reached maximum deceleration.
Crossing	Crossing decision	Binary	Decision made by the HDV to cross before (0) or after (1) the AV.
	Post Encroachment Time (PET)	s	Time headway between the HDV and AV at the moment when the HDV entered the intersection.
	Critical events	Binary	An interaction is classified as critical (1) if PET < 3 s or non-critical (0) if PET > 3 s.
Post-crossing	Crossing time	s	Time from when the AV was triggered to the time when the HDV crossed the intersection.

variables at different crossing stages. Definitions were adapted from the literature (Choudhary & Velaga, 2019; Devarasetty et al., 2012; Li et al., 2020; Pawar & Patil, 2018). Among these variables, Post Encroachment Time (PET) is a surrogate safety measure. An interaction was classified as critical if the PET score was less than 3 s, and non-critical if the PET score was greater than 3 s (FHWA, 2003; Gettman & Head, 2003; Peesapati et al., 2018).

5.4 Data cleaning and validation

Erroneous observations were identified and removed to improve data quality for the analysis and interpretations. Data also contained outliers due to diverse reasons. Irrelevant outliers were trimmed to increase the statistical power. The handling procedure is discussed below for erroneous observations and outliers.

5.4.1 Handling erroneous observations

Errors included response errors by participants, improper recording of data and participant bias. These errors reduced the validity of data. Hence, erroneous observations were either corrected or removed from the data. Erroneous observations were:

- Some of the perception questions were measured on a reverse order of scale to: reduce agreement bias and improve the complete measurement of opinions (Hopper, 2013). Three participants mentioned their response mistakes with reverse order questions. The comments were noted and later corrected.
- As the HDV did not have power steering, participants either crashed or lost control of vehicle for a brief period in 3 runs. The data of these participants was excluded.
- Behavior data for a couple of participants were incorrectly recorded. These observations were removed from the data.
- An older female participant, who did not have experience with driving simulator, took more than 40 minutes for the test drive. Due to time constraints, post-experiment phase was not completed. The post-experiment data of the participant was omitted.
- Experimental data of two female participants, who experienced simulator sickness symptoms, were excluded from the survey and behavior data.
- Few participants did not comply with the instructions and approached the trigger location with speeds higher than 60 kmph or less than 40 kmph in certain scenarios. These observations were removed from the data.

5.4.2 Handling outliers

Behavior data had outliers that were identified through the box and whisker plots. Some of these outliers belonged to the participants that were not compliant with AV intention. Results of Spearman correlations indicated that there was a significant negative correlation between non-compliance of HDV and perceived-interface quality of driving simulator when AV was non-yielding, $r = -.826$, $n = 10$, $p = .003$. Similarly, a negative but insignificant correlation existed when AV was yielding, $r = -.825$, $n = 5$, $p = .086$. These results imply that a lower perceived-interface quality increased the chance for HDVs' non-compliance, which led to outliers. However, there were few outliers that were not significantly affected by the interface quality. These outliers were found to be valid when verified through participant comments and research observations. Hence, these outliers existed in the behavior dataset. Median values of behavior variables were analysed to account for the outlier effect.

5.5 Overview of processed data

Processed survey data contained a CSV file with 132 rows and 32 columns. Each row represented observation for an individual scenario in the experiment. Survey data included pre-, mid-, and post-experiment data and AV preferences from the interview. Processed behavior data contained a CSV file with 12 columns and 607 rows, when AV was non-yielding and 569 rows, when AV was yielding. Each observation represented a valid AV-HDV interaction in the Table 5.

Table 5: Number of observations for driving behavior variables and scenarios in the final dataset. eHMI_V represents eHMI on vehicle and eHMI_I represents eHMI on infrastructure.

	AV non-yielding				AV yielding			
	Baseline	eHMI_V	eHMI_I	Total	Baseline	eHMI_V	eHMI_I	Total
Approaching speed (m/s)	203	200	204	607	192	187	190	569
Maximum acceleration (m/s^2)	203	200	204	607	192	187	190	569
Maximum deceleration (m/s^2)	203	200	204	607	192	187	190	569
Minimum speed (m/s)	203	200	204	607	192	187	190	569
Time to maximum braking (s)	203	200	204	607	192	187	190	569
Crossing decision (binary)	203	200	204	607	192	187	190	569
Critical events (binary)	203	200	204	607	192	187	190	569
Crossing time (s)	203	200	204	607	192	187	190	569

6 Analysis

Experimental data in different forms and stages were collected and processed, as discussed in section 5. The processed data were analysed to gain insights on driver perception and behavior in the interaction with AVs equipped with eHMIs.

As discussed in section 4.6, different analysis methods were implemented to answer the research questions. First, participant demographics were studied to understand the population sample in terms of driving knowledge, experience, and gender, among others. Second, a preliminary analysis was performed on the measured variables (i.e., perception and behavior) to understand the effect of eHMI conditions. Third, learning effects were studied between measured variables and the number of interactions in a scenario. Finally, modelling was applied to predict the effect of eHMI conditions on global traffic measures, such as traffic safety, efficiency of the AV-HDV interactions, and preferences for AVs.

6.1 Participant demographics

Forty-six participants (Male = 31; Female = 15) with driving experience between 2 and 53 years (*M*(*SD*) = 14.5(*14.7*)) participated in the experiment. Thirty-seven participants exhibited prosocial preferences, whereas the remaining participants demonstrated individualistic preferences. None of the participants expressed altruistic and competitive social preferences. Participants were fairly familiar (*M*(*SD*) = 3.7(*0.8*)) with the concepts of AVs and Advanced Driver Assistance Systems; where 35 reported experience with Cruise Control, 11 with Adaptive Cruise Control and the remaining with Lane Keeping Assistance. Among these participants, 47.8% were aged between 25 and 45 years and 34.8% were aged below 24 years. Thirty-seven participants completed PhD, Masters or equivalent, 5 participants completed bachelor's or equivalent and 4 participants completed Secondary education. 24 participants were full-time students, 17 were employed, 2 were nonworkers and 4 were retired. Participant driving exposure (kms/year) is represented in Figure 23.

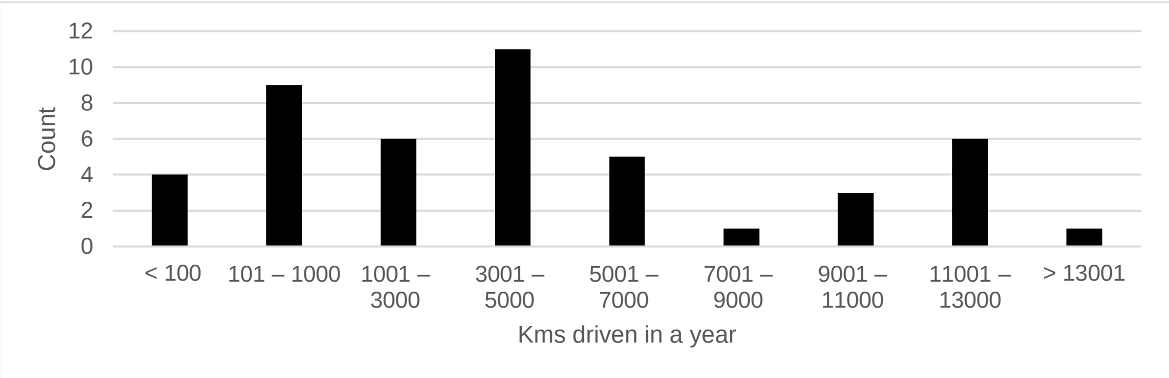


Figure 23: Histogram of average kilometres driven per year by the participants.

General trust on driverless car was measured before (*Mdn* = 3.8) and after (*Mdn* = 3.7) experiment using the Kaur & Rampersad (2018) questionnaire. No significance difference was indicated by a Wilcoxon signed-rank test, $T = 227.5$, $z = -1.209$, $p > .227$.

After the experiment, simulator fidelity was measured using the 19-item presence questionnaire by Jerome & Singer (2005). Questions on sound quality, localization and haptic fidelity were not applicable for this study. Overall, the scores in Figure 24 represented moderate virtual presence in comparison to Nuñez Velasco et al. (2019). Furthermore, simulator sickness was measured with the 16-item SSQ questionnaire (Kennedy et al., 1993) after the competition of the experiment. For all the categories of SSQ in Figure 25, the mean scores represented low severity of simulator sickness. No participants expressed severe sickness symptoms in the questionnaire responses.

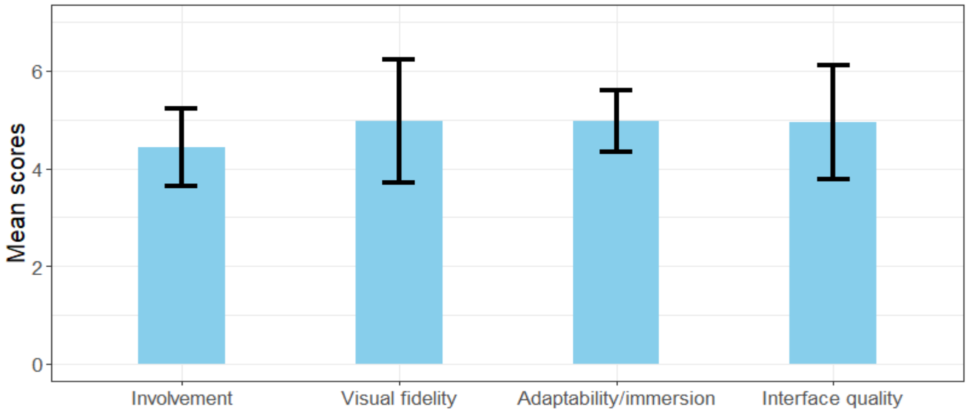


Figure 24: Presence questionnaire with error bars indicating SD. Involvement, visual fidelity, adaptability/immersion, interface quality are the contributing factors for presence. Scores range between 1 (no presence) to 7 (extreme presence).

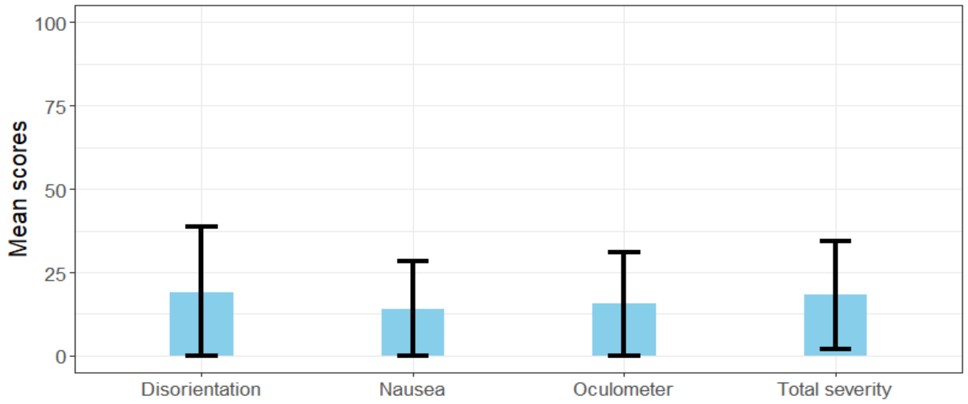


Figure 25: SSQ questionnaire with error bars indicating SD. Sickness symptoms include disorientation, nausea, oculomotor, and total severity. Scores range on a scale of 0 to 100. 0 to 25 = None, 25 to 50 = Slight, 50 to 75 = Moderate, 75 to 100 = Severe.

6.2 Preliminary analysis

Preliminary analysis, which contained descriptive and inferential statistics, aimed to study the effect of scenarios on driver perception and behavior. Descriptive analysis was performed through bar charts for categorical variables (nominal and ordinal) and box-violin plots for continuous variables (interval and ratio). Relevant inferential statistics were analysed through data formats and parametricity. Data format of perception and behavior variables is illustrated in Table 6. Data parametricity is discussed in section 6.2.1.

Table 6: Data formats of perception and behavior variables.

Data format	Perception and behavior variables
Nominal	Crossing decision, critical events
Ordinal	Perceived criticality, trust, user acceptance, emotions, NASA-TLX workload
Ratio	Approaching speed, maximum acceleration, maximum deceleration, minimum speed, time to maximum braking, crossing time

6.2.1 Statistical tests

Statistical tests differ in data format, parametricity, and the number of observations (Soni, 2020). The appropriate steps and methods were identified from the literature (Garth, 2008; McCrum-Gardner, 2008; Sheskin, 2003; Siegel, 1956). Initially, the distribution of perception and behavior data was checked for normality. Shapiro and Kolmogorov-Smirnov tested the null hypothesis for normality: no difference exists between variable (i.e., perception and behavior) distribution and normal distribution. Results from normality tests rejected null hypothesis at 95% confidence level (i.e., $p < 0.05$). Hence, perception and behavior data were treated as not normally distributed.

Statistical tests include parametric and non-parametric tests. Perception and behavior data required non-parametric tests as the data was not-normal. In addition, the data were paired as each participant was subjected to three scenarios or eHMI conditions. Before performing the statistical tests, data were averaged for multiple interactions over the scenario and AV driving style. Data of each participant represented an observation in the dataset. This technique reduced the random variations in the data due to unexplored factors (Soni, 2020).

6.2.2 Analysis of perception variables

Our research studies the effect of eHMIs on AV-HDV communicative interactions, which are measured in driver perception and behavior, as discussed in section 2. This section focuses on analysing the effect of eHMI conditions on driver perception variables. Significant effects were identified with non-parametric statistical tests. Table 7 presents the Friedman test results for different driver perception variables within scenarios. Perceived criticality, trust, user acceptance (usefulness and satisfaction), emotions (pleasure and arousal), workload (mental demand) and preferences had significant differences with eHMI conditions. Significant perception variables were further subjected to a post-hoc test (i.e., Wilcoxon signed rank test) to study the pairwise comparisons. These results are reported in Table 8 with Bonferroni correction. The correction reduces the probability of type-I errors that arise due to multiple statistical tests. The obtained results are discussed below.

Table 7: Overview of Friedman test results for the perception variables over scenarios. Critical p-value is 0.05. Asterisks indicate significant p-values. The mean ranks vary with number of conditions (i.e., 1 for the smallest variable score and 3 for the largest variable score). eHMI_V represents eHMI on vehicle. eHMI_I represents eHMI on infrastructure. Workload performance is measured on an inverted scale where the highest and least scores represent low and high performance, respectively. Similar inverted scale applies for preference.

Variables		Mean ranks			Z	P-value
		Baseline	eHMI_V	eHMI_I		
Perceived Criticality		2.31	1.81	1.89	7.503	0.023*
Trust		1.35	2.35	2.30	30.924	<0.001*
User acceptance	Usefulness	1.32	2.39	2.30	34.38	<0.001*
	Satisfaction	1.43	2.27	2.30	23.018	<0.001*
Emotions	Pleasure	1.50	2.23	2.27	21.412	<0.001*
	Arousal	2.45	1.95	1.59	23.484	<0.001*
	Dominance	1.89	2.01	2.10	1.583	0.453
Workload	Mental demand	2.35	1.73	1.92	10.232	0.006*
	Physical demand	2.24	1.86	1.90	5.163	0.076
	Temporal demand	2.06	1.78	1.95	3.280	0.194
	Performance	2.09	1.99	1.92	1.018	0.601
	Frustration	2.26	1.91	1.83	5.641	0.060
	Effort	2.25	1.90	1.85	5.133	0.077
	Overall workload	2.28	1.80	1.92	5.836	0.054
Preference for AVs		2.77	1.52	1.70	40.136	<0.001*

Table 8: Post hoc test results for the significant perception variables scenarios. Significant perception variables are selected from Table 7. The p-value denotes the significance with a Bonferroni correction (p-values were multiplied by the number of hypotheses of 3). The critical p-value is 0.05. Asterisks indicate significant p-values. eHMI_V represents eHMI on vehicle. eHMI_I represents eHMI on infrastructure.

Variables		Pairs	Z	P-value
Perceived Criticality		Baseline - eHMI_V	-2.248	0.074
		Baseline - eHMI_I	-1.262	0.621
		eHMI_V - eHMI_I	-.924	1.067
Trust		Baseline - eHMI_V	-4.279	<0.001*
		Baseline - eHMI_I	-4.529	<0.001*
		eHMI_V - eHMI_I	-.075	2.821
User acceptance	Usefulness	Baseline - eHMI_V	-5.006	<0.001*
		Baseline - eHMI_I	-4.594	<0.001*
		eHMI_V - eHMI_I	-.792	1.284
	Satisfaction	Baseline - eHMI_V	-4.543	<0.001*
		Baseline - eHMI_I	-4.308	<0.001*
		eHMI_V - eHMI_I	-.046	2.891
Emotions	Pleasure	Baseline - eHMI_V	-3.877	<0.001*
		Baseline - eHMI_I	-4.209	<0.001*
		eHMI_V - eHMI_I	-.287	2.322
	Arousal	Baseline - eHMI_V	-3.074	0.006*
		Baseline - eHMI_I	-3.909	<0.001*
		eHMI_V - eHMI_I	-2.524	0.035*
Workload	Mental demand	Baseline - eHMI_V	-2.535	0.034*
		Baseline - eHMI_I	-2.201	0.083
		eHMI_V - eHMI_I	-.785	1.297
Preference for AVs		Baseline - eHMI_V	-5.118	<0.001*
		Baseline - eHMI_I	-4.707	<0.001*
		eHMI_V - eHMI_I	-1.023	0.919

Perceived criticality

The results of the perceived criticality showed no dangerous interactions (i.e., scores above 7) for all the three scenarios. Figure 26 depicts the mean (SD) perceived criticality for the

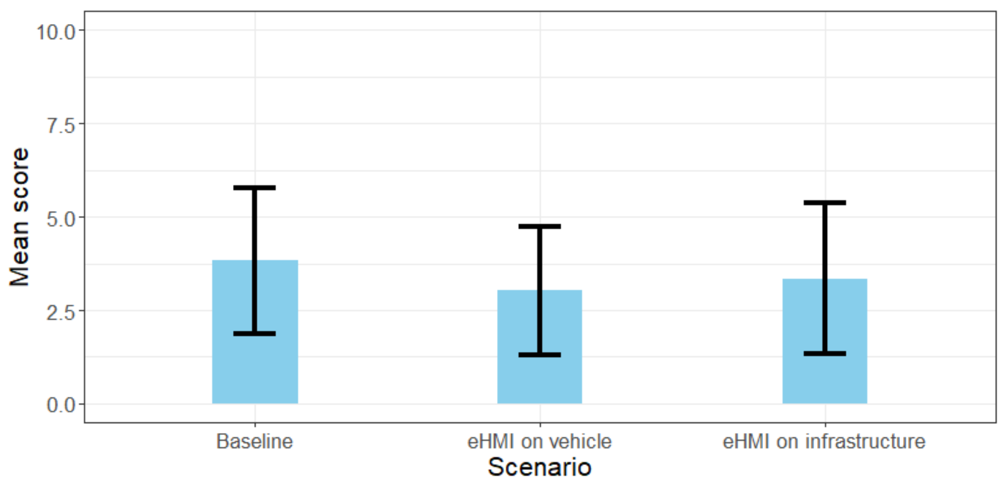


Figure 26: Perceived criticality scores over scenarios with error bars indicating standard deviation (SD). On a scale of 1 to 10, 1 represents harmless interaction and 10 represents uncontrollable interaction.

baseline, eHMI on vehicle (eHMI_V) and eHMI on infrastructure (eHMI_I) conditions. Mean scores explained that criticality of eHMI_V (*M* = 2.9, *SD* = 1.6) and eHMI_I (*M* = 3.3, *SD* = 2.0) conditions was perceived lower than baseline condition (*M* = 3.8, *SD* = 1.9), respectively. Interactions in eHMI_V condition were classified as harmless based on mean scores (for procedure see section 5.2.2), whereas interactions in eHMI_I and baseline conditions were classified as unpleasant experiences. Pairwise comparisons with Bonferroni correction, however, showed no statistically significant differences among the three conditions (see Table 8).

Trust

Figure 27 exhibited a gradually higher trust for eHMI_V (*M* = 7.1, *SD* = 1.7) and eHMI_I (*M* = 7.2, *SD* = 1.8) conditions, when compared to baseline (*M* = 4.9, *SD* = 2.1) condition. Significant differences existed in trust on AVs over eHMI conditions using Friedman's test (see Table 7). Post hoc analysis (see Table 8) showed a statistically significant difference for the baseline condition with the eHMI_V and eHMI_I conditions. However, no significant difference (see Table 8) was observed in the reported trust between eHMI_V and eHMI_I conditions.

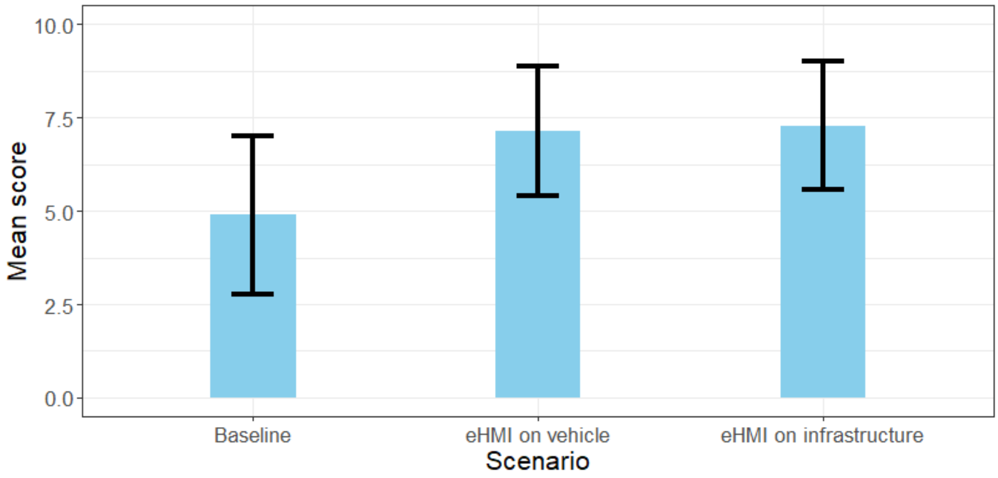


Figure 27: Reported trust scores on AVs for the three scenarios. On a scale of 1 to 10, 1 represents no trust on AVs and 10 represents extremely high trust on AVs. Error bars indicate SD.

User acceptance

Friedman's test results showed that user acceptance, measured in usefulness and satisfaction, was significantly different among the three scenarios (see Table 7). The mean (*SD*) usefulness scores (see Figure 28) for the baseline, eHMI_V, eHMI_I scenarios was -0.2(*0.8*), 0.7(*0.6*), and 0.6(*0.6*), respectively. On the other hand, the mean (*SD*) satisfaction scores (see Figure 28) for the baseline, eHMI_V, eHMI_I scenarios was -0.1(*0.9*), 0.8(*0.7*), and 0.7(*0.8*), respectively. Similar variation in scenarios was observed for usefulness and satisfaction scores. Post hoc analysis (see Table 8) and mean scores showed significantly higher usefulness and satisfaction scores for eHMI_V and eHMI_I than baseline scenario. However, post hoc analysis (see Table 8) exhibited no significant difference in the usefulness and satisfaction scores between eHMI_V and eHMI_I scenarios.

Emotions

Emotions were measured in three dimensions: pleasure, arousal, and dominance. Friedman's test results showed that pleasure and arousal were significantly different within the scenarios (see Table 7). The mean (*SD*) pleasure scores (see Figure 29) for the baseline, eHMI_V, eHMI_I conditions was 4.9(*1.7*), 6.5(*1.5*), and 6.4(*1.4*), respectively. Post hoc analysis (see Table 8) and mean scores showed significantly higher pleasure scores for eHMI_V and eHMI_I than baseline conditions. However, post hoc analysis (see Table 8) exhibited no significant difference in the pleasure scores between eHMI_V and eHMI_I scenarios.

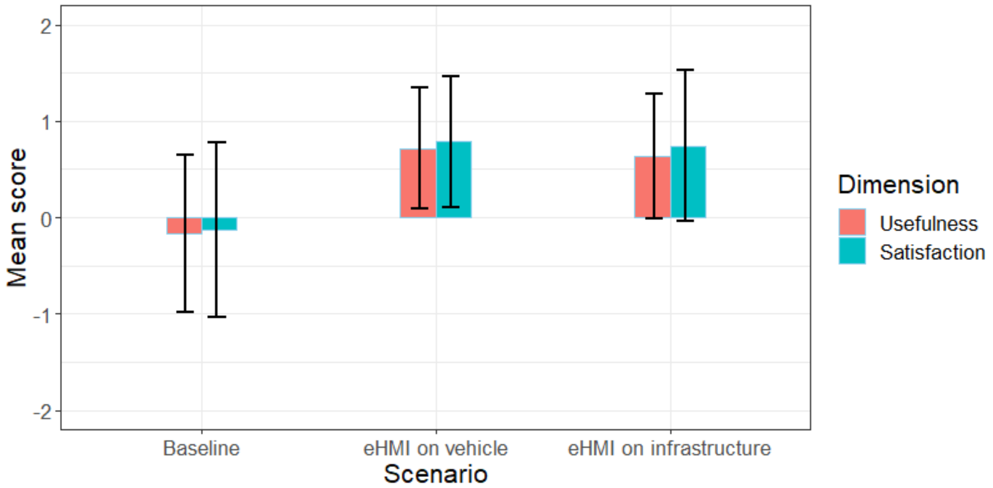


Figure 28: Scores on the user acceptance, which includes usefulness and satisfaction, for three scenarios. On a scale of -2 to +2, +2 represents highly acceptable and -2 represents unacceptable eHMI condition. Error bars indicate SD.

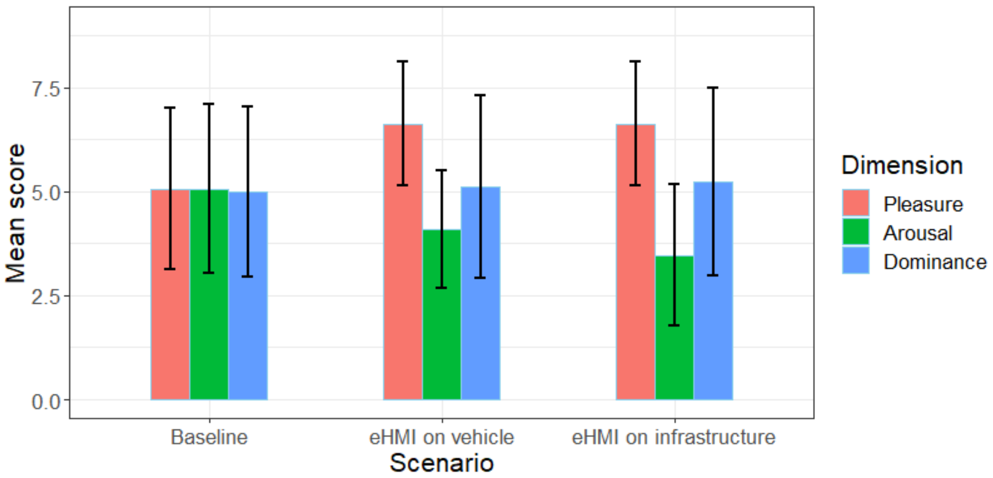


Figure 29: Scores on the emotions, including pleasure, arousal, and dominance, for the three scenarios. On a scale of 1 to 9, 1 represents no experience, and 9 represents the full experience of an emotion. Error bars indicate SD.

Post hoc analysis (see Table 8) and mean scores (see Figure 29) showed significant differences among the three scenarios for the arousal scores. The lowest arousal score (*M* = 3.7, *SD* = 1.6) was observed for eHMI_I, whereas the highest arousal score (*M* = 5.0, *SD* = 1.9) was observed for baseline among the three scenarios (see Figure 29). The mean arousal score for the eHMI_V scenario (*M* = 4.2, *SD* = 1.2) was significantly higher than eHMI_I scenario (*M* = 3.7, *SD* = 1.6), and significantly lower than baseline scenario (*M* = 4.9, *SD* = 2.1).

The mean (*SD*) dominance scores (see Figure 29) for the baseline, eHMI_V, eHMI_I scenarios was 5.0(*1.9*), 5.1(*2.0*), and 5.3(*2.1*), respectively. Participants experienced slightly higher mean dominance in eHMI_I than eHMI_V and baseline scenarios.

Friedman's test results, however, showed that dominance scores were not significantly different among the three scenarios (see Table 7).

NASA-TLX workload

NASA-TLX workload (see Figure 30) was measured in mental demand, physical demand, temporal demand, performance, frustration, effort, and overall workload. Among these measurers, mental demand was significantly different among the three scenarios using Friedman's test (see Table 7). Mean scores in Figure 30 showed lower mental demand scores for eHMI_V (*M* = 44.8%, *SD* = 22.5), and eHMI_I (*M* = 46.8%, *SD* = 22.2) than baseline scenario (*M* = 57.1%, *SD* = 23.6).

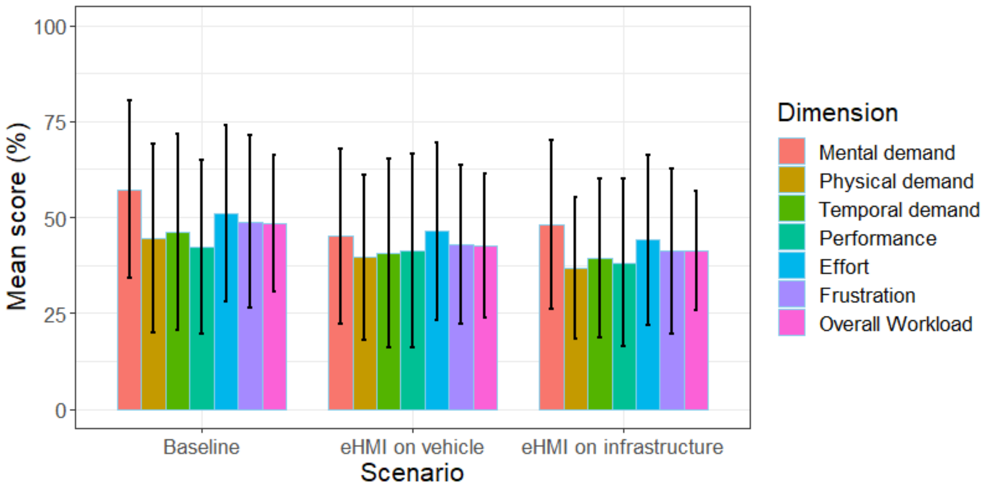


Figure 30: Scores on the NASA-TLX workload for the three scenarios. The scores are represented as a percentage and vary from Very low (0%) to Very high (100%) for the mental demand, physical demand, temporal demand, frustration, and effort dimensions, and from perfect (0%) to failure (100%) for the performance dimension. Error bars indicate SD.

Post hoc analysis confirmed a significantly lower mental demand score for eHMI_V than the baseline scenario by 12.4% (see Table 8). However, post hoc analysis (see Table 8) exhibited no significant difference in the mental demand scores between the scenario pairs: eHMI_V vs eHMI_I, and baseline vs eHMI_I.

The mean (*SD*) scores of the remaining workload dimensions for the baseline, eHMI_V, eHMI_I scenarios were illustrated in Figure 30. In comparison to the baseline, eHMI_V and eHMI_I recorded slightly lower mean scores in physical demand, temporal demand, performance (measured on an inverted scale), frustration, effort, and overall workload. Fridman's test observed that the above workload scores were not significantly different among the three scenarios (see Table 7).

Preference for AVs

Participant preferences for AVs with different eHMIs were illustrated in Figure 31. In total, 95.45% of participants preferred AVs with at least one form of eHMI. Two participants (4.55%) expressed high preference for baseline, 24 participants (54.55%) for eHMI_V, and 18 participants (40.9%) for eHMI_I conditions. On the other hand, 36 participants (81.82%) least preferred baseline, 3 (6.82%) for eHMI_V, and 5 (11.36%) for eHMI_I conditions. AVs with eHMIs were highly preferred over the baseline condition. Friedman's test results showed a significant difference in preferences among the three scenarios (see Table 7). Post hoc analysis (see Table 8) showed a significantly higher preference for AVs with eHMI_V, and eHMI_I than the baseline condition. No significant differences were observed in preference for AVs between eHMI_V and eHMI_I conditions using post hoc analysis (see Table 8).

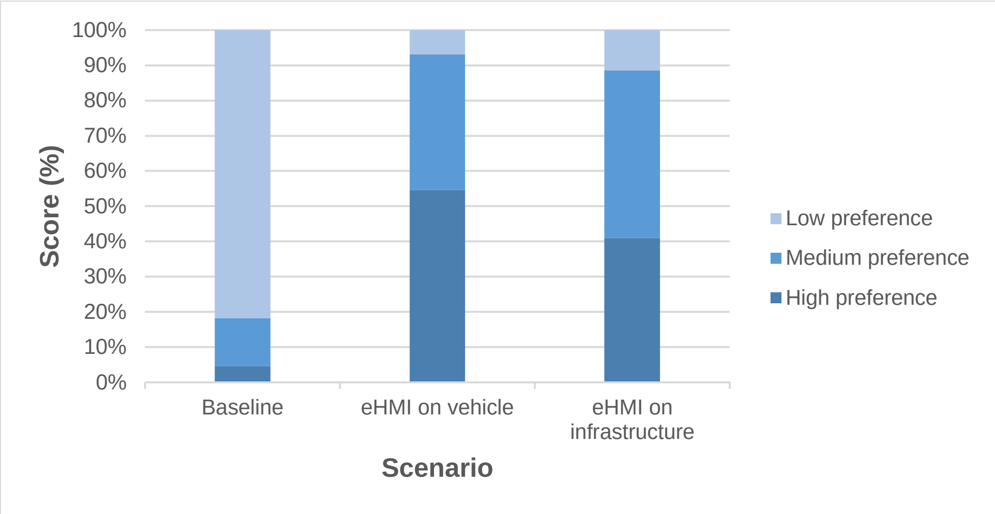


Figure 31: Participant preferences (%) for AVs with different scenarios.

6.2.3 Analysis on behavior variables

Behavior variables were calculated for each participant interaction over different scenarios and AV driving styles, as discussed in section 5.3. Figure 32 illustrates the inter-vehicle distance perceived by a participant with AVs over different driving styles and crossing stages in a scenario. The inter-vehicle distance between HDV and AV is lower with non-yielding than yielding behavior. The inter-vehicle distance decreases as the driver approaches and crosses the intersection.

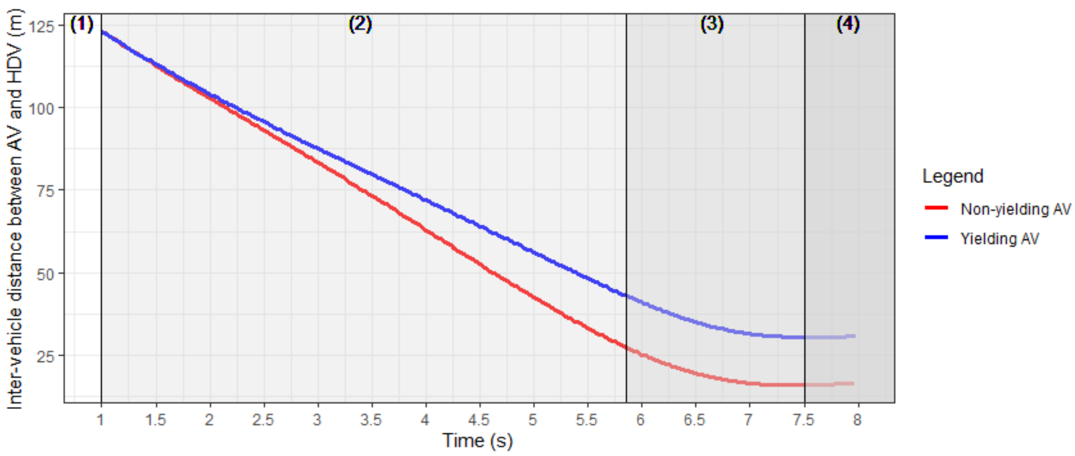


Figure 32: Inter-vehicle distance between AV and HDV over driving style and crossing stages. The HDV is driven by participant 5 in scenario 1 for interaction 3 with yielding AV, and interaction 7 with non-yielding AV. In both the interactions, participant crossed before the AV. (1) represents the period in which the participant is approaching the trigger location, (2) shows the period when the participant is in the pre-crossing stage, (3) is the period when the participant is in crossing stage, and (4) represents the period in which the participant exited the intersection.

The behavior variables were subjected to box-violin plots and non-parametric statistical tests to identify the effect of eHMIs. The results were reported in this section. Friedman's test (see Table 9) was performed to identify the variables that differ significantly with eHMIs. Post hoc analysis was performed for the significant variables with Wilcoxon paired rank test and Bonferroni correction (see Table 10).

Table 9: Overview of Friedman's test results for driver behavior variables over eHMI conditions and AV driving style. Critical p-value is 0.05. Asterisks indicate significant p-values. The mean ranks vary with the number of groups (i.e., 1 for the smallest variable score and 3 for the largest variable score). eHMI_V represents eHMI on vehicle. eHMI_I represents eHMI on infrastructure.

		Non-Yielding					Yielding				
Crossing stage	Variables	Mean ranks			Z	P-value	Mean ranks			Z	P-value
		Baseline	eHMI_V	eHMI_I			Baseline	eHMI_V	eHMI_I		
Pre-crossing	Approaching speed	2.34	2.12	1.55	66.7	<0.001*	1.98	2.07	1.95	0.495	0.474
	Maximum acceleration	1.92	1.98	2.1	3.22	0.2	2.02	1.87	2.11	5.857	0.053
	Maximum deceleration	2.03	2.07	1.9	3.22	0.2	1.96	2.03	2.01	0.476	0.789
	Minimum speed	2.08	2.04	1.88	4.48	0.106	1.95	2.06	1.98	1.258	0.533
	Time to maximum braking	2.29	1.9	1.82	24.9	<0.001*	2	2.04	1.96	0.527	0.768
Crossing	Crossing decision	2.06	1.96	1.98	4.2	0.122	1.89	2.05	2.06	27.793	<0.001*
	Critical events (from PET)	1.71	2.1	2.2	26.8	<0.001*	1.64	2.02	2.34	45.559	<0.001*
Post-crossing	Crossing time	1.89	1.87	2.25	18	<0.001*	2.05	1.92	2.03	1.882	0.39

Table 10: Post hoc test results for the significant behavior variables over scenarios. Significant perception variables are selected from Table 9. The p-value is the significance with a Bonferroni correction (p-values were multiplied by the number of hypotheses of 3). The critical p-value is 0.05. Asterisks indicate significant p-values. eHMI_V represents eHMI on vehicle. eHMI_I represents eHMI on infrastructure.

		Non-Yielding		Yielding		
Crossing stages	Variable	Pairs	Z	P-value	Z	P-value
Pre-crossing	Approaching speed	Baseline - eHMI_V	-2.703	0.021*	-	-
		Baseline - eHMI_I	-6.526	<0.001*	-	-
		eHMI_V - eHMI_I	-4.105	<0.001*	-	-
	Time to maximum braking	Baseline - eHMI_V	-3.473	0.002*	-	-
		Baseline - eHMI_I	-4.256	<0.001*	-	-
		eHMI_V - eHMI_I	-.685	1.480	-	-
Crossing	Crossing decision	Baseline - eHMI_V	-	-	-3.800	<0.001*
		Baseline - eHMI_I	-	-	-4.426	<0.001*
		eHMI_V - eHMI_I	-	-	-.707	1.439
	Critical events (from PET)	Baseline - eHMI_V	-5.088	<0.001*	-4.519	<0.001*
		Baseline - eHMI_I	-5.712	<0.001*	-7.638	<0.001*
		eHMI_V - eHMI_I	-1.536	0.374	-3.964	<0.001*
Post-crossing	Crossing time	Baseline - eHMI_V	-.592	1.661	-	-
		Baseline - eHMI_I	-4.026	<0.001*	-	-
		eHMI_V - eHMI_I	-3.199	0.004*	-	-

Pre-crossing stage

Approaching speed, maximum acceleration, maximum deceleration, minimum speed, and time to maximum braking were the analysed variables in this stage. Preliminary analysis results were reported below. The results were segregated for each AV driving style.

Approaching speed

Approaching speed profiles of HDVs (see Figure 33 and Figure 34) were generated for every 5m interval in the approach distance (i.e., distance from trigger location to the start of intersection). The speed profiles were analysed to briefly understand the effect of eHMIs. A general observation, approaching speed of HDV varied in eHMI scenarios when compared to the baseline.

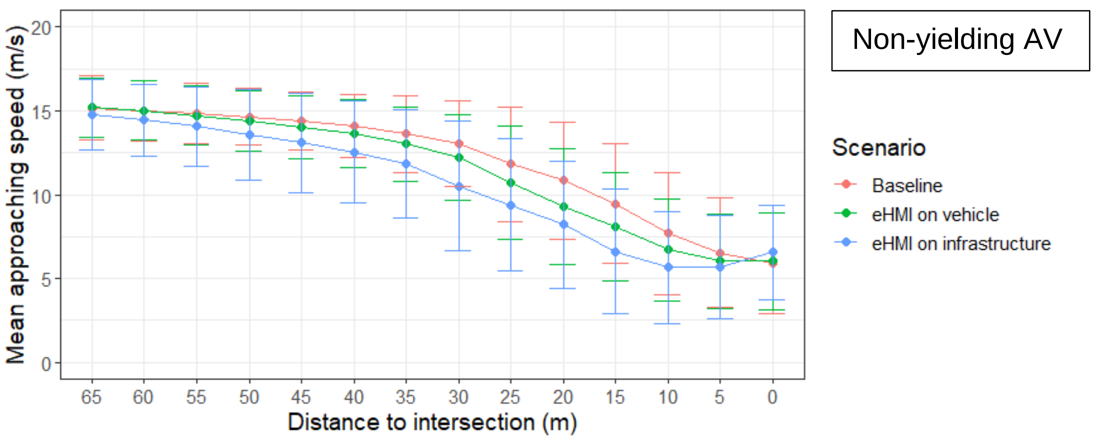


Figure 33: Approaching speed profile of HDVs for three scenarios where AV is not yielding at the intersection. Error bars indicate SD.

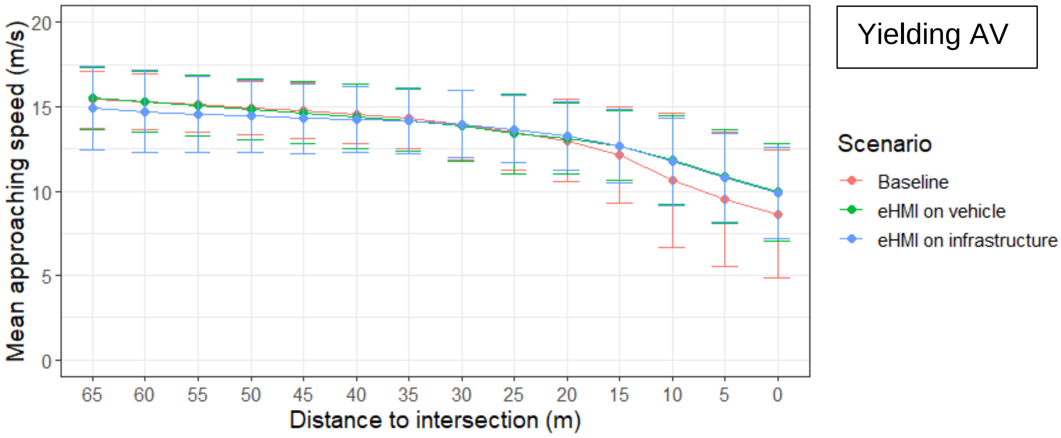


Figure 34: Approaching speed profile of HDVs for three scenarios where AV is yielding at the intersection. Error bars indicate SD.

When the AV was not yielding, HDVs approached the intersection with a lower mean speed in the eHMI_V and eHMI_I scenarios than baseline in Figure 33. For a yielding AV in Figure 34, however, the difference in mean approaching speed was less pronounced among the three scenarios. In order to understand the mean approaching speed of HDVs over the approach distance to the intersection, the box-violin plot is illustrated in Figure 35.

Non-yielding: Mean approaching speed of participants was the highest in the baseline condition, and the least in the eHMI_I scenario in Figure 35. The approaching speed of HDVs in the eHMI_V scenario was gradually lower than baseline by 0.34 m/s, and higher than eHMI_I by 0.54 m/s. Friedman test results (see Table 9) showed significant differences in the approaching speed within the three scenarios. Post hoc analysis (see Table 10) showed significant differences between the scenario pairs: baseline vs eHMI_I; baseline vs eHMI_V; eHMI_I vs eHMI_V.

Yielding: Mean approaching speed is illustrated in Figure 35 for the baseline, eHMI_I, eHMI_V

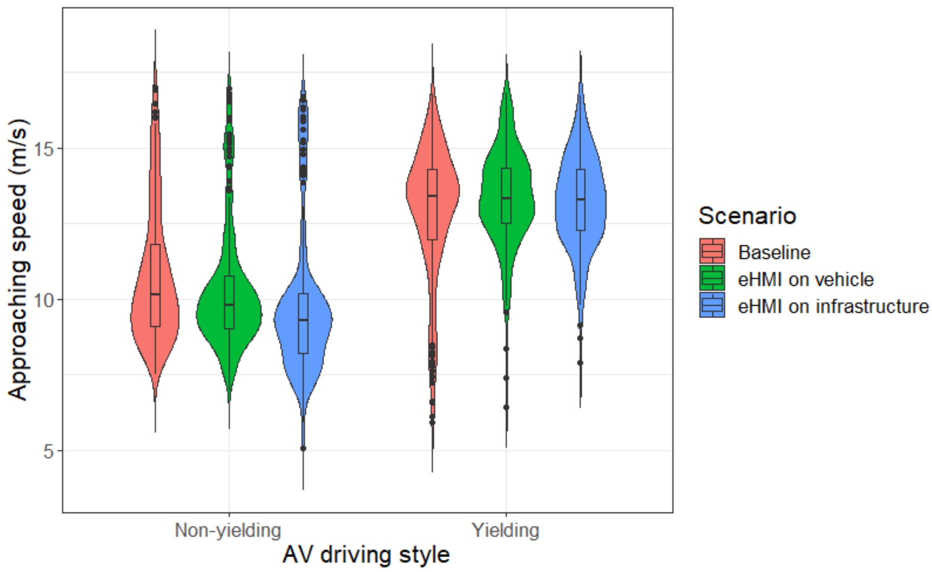


Figure 35: Approaching speed (m/s) of participants over the scenarios and the AV driving styles. The approaching speed is represented with a box-violin plot with outliers.

scenarios. In comparison to the baseline, mean approaching speed was slightly lower in eHMI_V and eHMI_I by 0.06 m/s and 0.11 m/s, respectively. The approaching speed was slightly higher in the eHMI_V than eHMI_I. Friedman test (see Table 9) showed that the approaching speed in the three scenarios was not significantly different.

Maximum acceleration

Non-yielding: The maximum acceleration in the baseline scenario was 2.15 m/s^2, increased to 2.57 m/s^2 for eHMI_V, and 2.90 m/s^2 for eHMI_I in Figure 36. The highest maximum acceleration was observed in eHMI_I among the three scenarios. Friedman's test results showed no significant difference among the three conditions in Table 9.

Yielding: In accordance with the above result, maximum acceleration of the eHMI_I was 0.5 m/s^2, slightly higher than eHMI_V by 0.15 m/s^2, and baseline by 0.2 m/s^2 in Figure 36. No major difference was observed between eHMI_V and baseline scenarios. The maximum acceleration in the three scenarios was not significantly different using Friedman's test in Table 9.

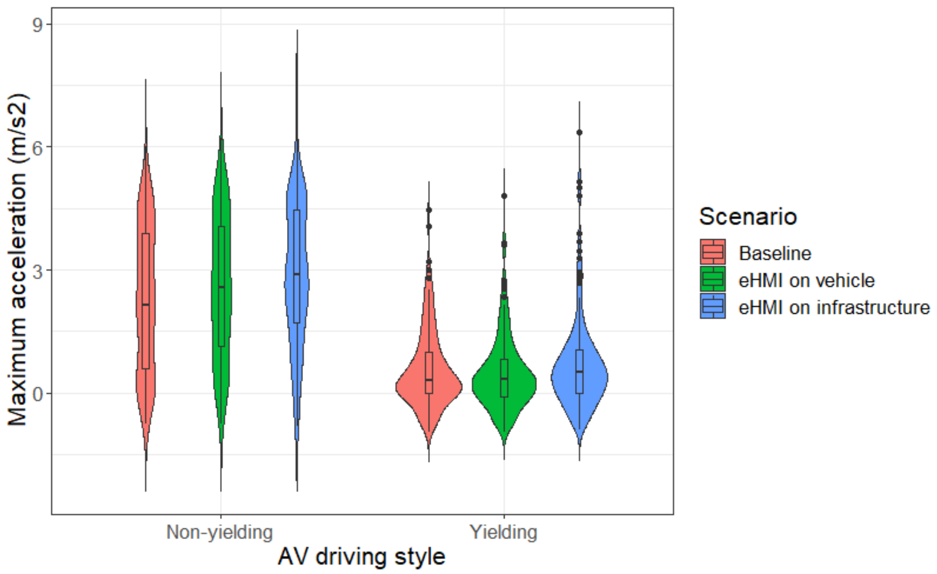


Figure 36: Maximum acceleration (m/s^2) of participants over the scenarios and the AV driving styles. The maximum acceleration is represented with a box-violin plot with outliers.

Maximum deceleration

Non-yielding: The maximum deceleration of HDVs (see Figure 37) depicted a lower value for the eHMI_V condition than eHMI_I and baseline by 0.6 m/s^2 and 0.9 m/s^2, respectively. Slightly lower maximum deceleration was observed in the eHMI_I condition than the baseline by 0.3 m/s^2. Friedman test results in Table 9 reported that the three conditions were not statistically different.

Yielding: On similar lines with the above results of maximum deceleration, eHMI_V condition obtained the lowest value of -3.56 m/s^2 among the three scenarios in Figure 37. HDVs in the eHMI_I condition, however, had a gradually higher maximum deceleration of 0.05 m/s^2 than the baseline condition. Friedman's test results exhibited no significant difference among the three scenarios in Table 9.

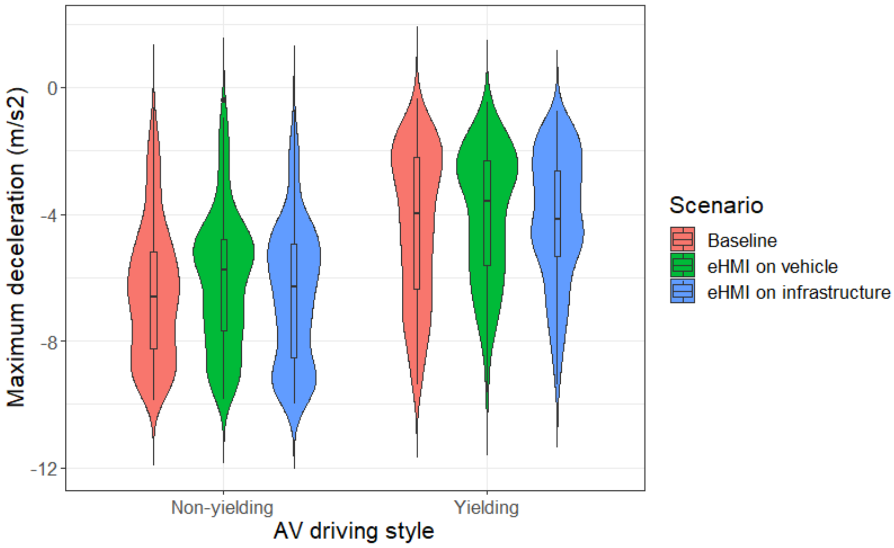


Figure 37: Maximum deceleration (m/s^2) of participants over the scenarios and the AV driving styles. The maximum deceleration is represented with a box-violin plot with outliers.

Minimum speed

Non-yielding: Minimum speed of participants in the eHMI_V scenario was higher than eHMI_I and baseline by 0.22 m/s and 0.2 m/s, respectively in Figure 38. No major difference existed in the minimum speed of HDVs between the eHMI_I and baseline scenarios. No significant differences among the three scenarios were observed in Table 9 using Friedman's test.

Yielding: On similar lines with the above result, participants maintained a higher minimum speed in the eHMI_V scenario than eHMI_I by 0.39 m/s, and baseline by 0.44 m/s in Figure 38. Friedman's test results in Table 9 showed no significant differences in minimum speed among the three conditions.

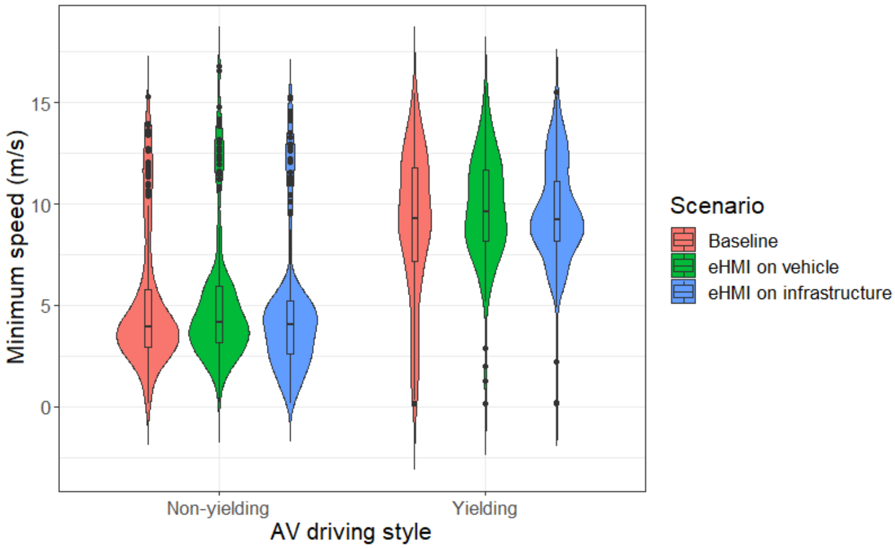


Figure 38: Minimum speed (m/s) of participants over the scenarios and the AV driving styles. The minimum speed is represented with a box-violin plot with outliers.

Time to maximum braking

Non-yielding: Box-violin plot (see Figure 39) depicted that the time to maximum braking for the baseline condition was higher than eHMI_V and eHMI_I by 0.15 s and 0.23 s, respectively.

HDVs took the least time to brake in the eHMI_I condition among the three scenarios in Figure 39. Friedman's test (see Table 9) showed significant differences for the three scenarios. Post hoc analysis in Table 10 showed statistically significant differences for the scenarios: baseline vs eHMI_I; baseline vs eHMI_V. Post hoc analysis reported no significant differences between the eHMI_I and eHMI_V conditions in Table 10.

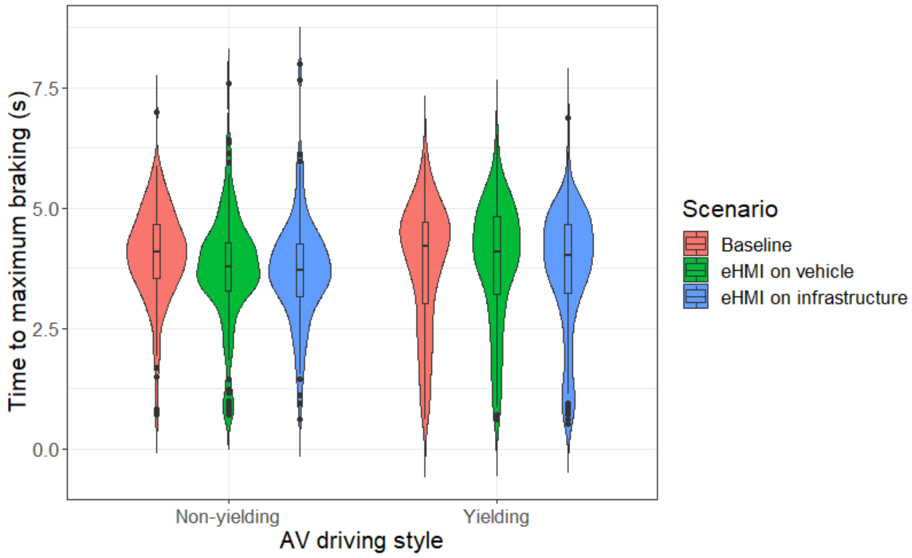


Figure 39: Box-violin plot for time to maximum braking (s) over the scenarios and the AV driving styles. The box-violin plot contains outliers.

Yielding: In line with the above result, the baseline scenario had higher time to maximum braking than eHMI_V and eHMI_I scenarios in Figure 39. On the other hand, HDVs in the eHMI_V scenario had slightly lower time to maximum braking than baseline by 0.15 s and eHMI_I by 0.08 s. Friedman's test in Table 9 showed that the three conditions were not significantly different.

Crossing stage

Crossing decision and critical events (from PET) were the analysed variables in this stage. The results are reported below.

Crossing decision

Crossing decision of HDV was initially measured in 0 (yielding) and 1 (crossing) for each interaction with AV. As the observations over multiple interactions were averaged for a participant (see section 6.2.1), crossing decision was transformed into a proportion measure for HDVs crossed before AV. This estimation was performed for each eHMI condition and AV driving style.

Non-yielding: The proportion of HDVs crossed before AVs (see Figure 40) for the baseline scenario was 18.6%, which decreased to 12.5%, and 13.4% for the eHMI_V and eHMI_I scenarios, respectively. Friedman's test (see Table 9) showed that the three scenarios were not significantly different.

Yielding: The proportion of HDVs crossed before AVs (see Figure 40) for the baseline scenario was 86.2%, increased to 96.8%, and 97.9% for the eHMI_V and eHMI_I scenarios, respectively. The three scenarios were significantly different using Friedman's test in Table 9. Post hoc analysis (see Table 10) showed statistically significant differences between the scenarios: baseline vs eHMI_I; baseline vs eHMI_I. No significant difference existed between the eHMI_V and eHMI_I scenarios.

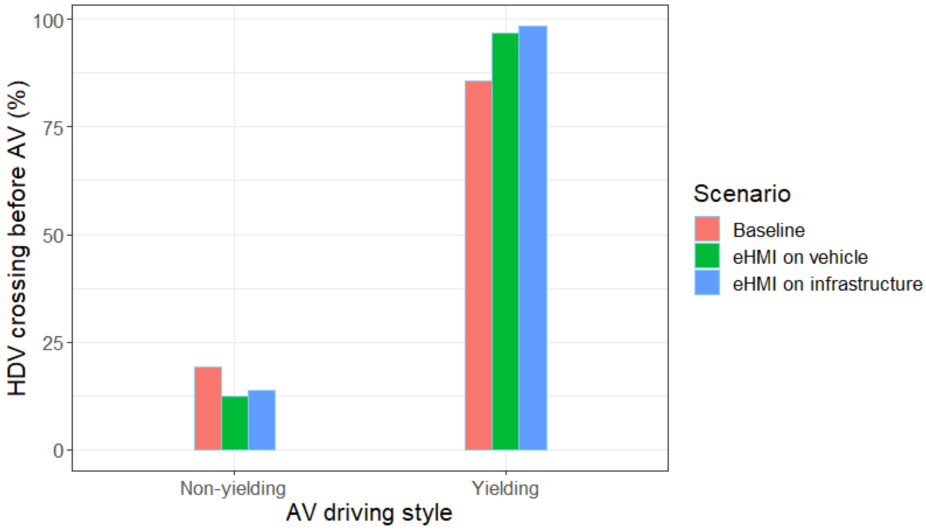


Figure 40: Bar chart for HDV decision to cross before AV (%) over the scenarios and the AV driving styles.

Critical events

PET scores were used to classify the AV-HDV interactions as critical events in terms of 0 (not critical) and 1 (critical). The critical events for multiple interactions were transformed as proportions for each participant, similar to crossing decision. Figure 41 illustrates the crossing decision for the scenarios and AV driving styles.

Non-yielding: The proportion of critical events (see Figure 41) in the baseline scenario was 87.7%, decreased to 66%, and 70.1% for the eHMI_V, and eHMI_I scenarios, respectively. eHMI_V had the least proportion of critical events among the three scenarios, whereas baseline condition had the highest proportion. There were significantly differences in the proportion of critical events among the three scenarios using Friedman's test (see Table 9).

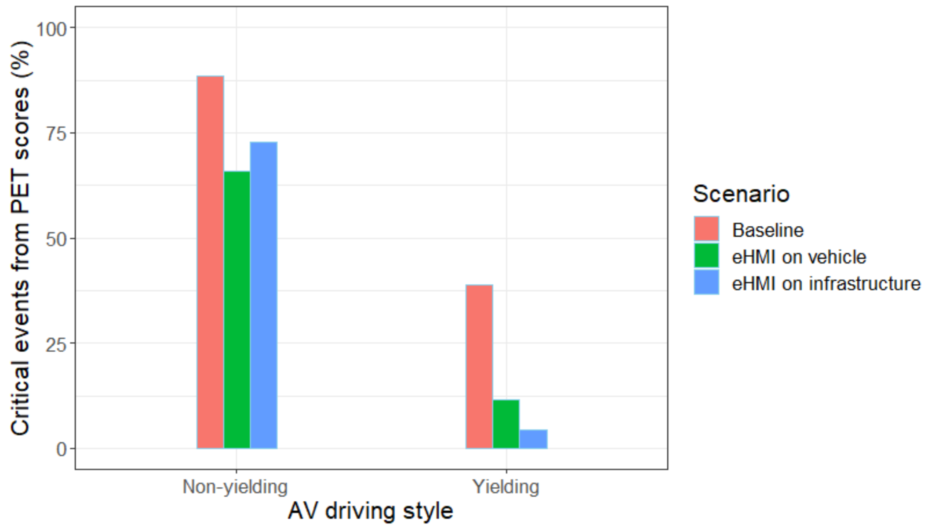


Figure 41: Bar chart for critical events from PET (%) over the scenarios and the AV driving styles. An interaction is considered as critical if the PET score < 3s, else non-critical if the PET score > 3s.

Post hoc analysis (see Table 10) showed statistically significant differences between the scenario pairs: baseline vs eHMI_I; baseline vs eHMI_V. However, the differences were not statistically significant between the eHMI_I and eHMI_V scenarios with the post hoc test (see Table 10).

Yielding: The proportion of critical events (see Figure 41) for the baseline scenario was 39.5%, reduced to 12.4%, and 5.9% for the eHMI_V, and eHMI_I scenarios, respectively. The baseline scenario had a higher proportion of critical events over the two scenarios, which is similar to non-yielding AV. On the other hand, eHMI_I had the lowest proportion of critical events among the three scenarios. Friedman's test results (see Table 9) showed significant differences in the proportion of critical events among the scenarios. Post hoc analysis (see Table 10) showed significant differences between the pairs: baseline vs eHMI_I; baseline vs eHMI_V; eHMI_I vs eHMI_V.

Post-crossing stage

Crossing time

Non-yielding: The crossing time of HDVs (see Figure 42) in the eHMI_I scenario was higher than the baseline and eHMI_V by 0.22 s and 0.33 s, respectively. HDVs in eHMI_V had slightly lower crossing time than baseline by 0.11 s. Friedman's test results (see Table 9) showed the crossing time was different in the three scenarios. The results of post hoc analysis (see Table 10) showed that HDVs in the eHMI_I condition had a statistically significant difference with the eHMI_V and baseline conditions. However, the difference between the two scenarios (i.e., eHMI_I vs eHMI_V) were not statistically significant in Table 10.

Yielding: The crossing time of HDVs in the baseline scenario was 7.64 s, decreased to 7.55 s for eHMI_V, and 7.63 s for eHMI_I in Figure 42. Friedman's test results showed no significant differences among the three scenarios in Table 9.

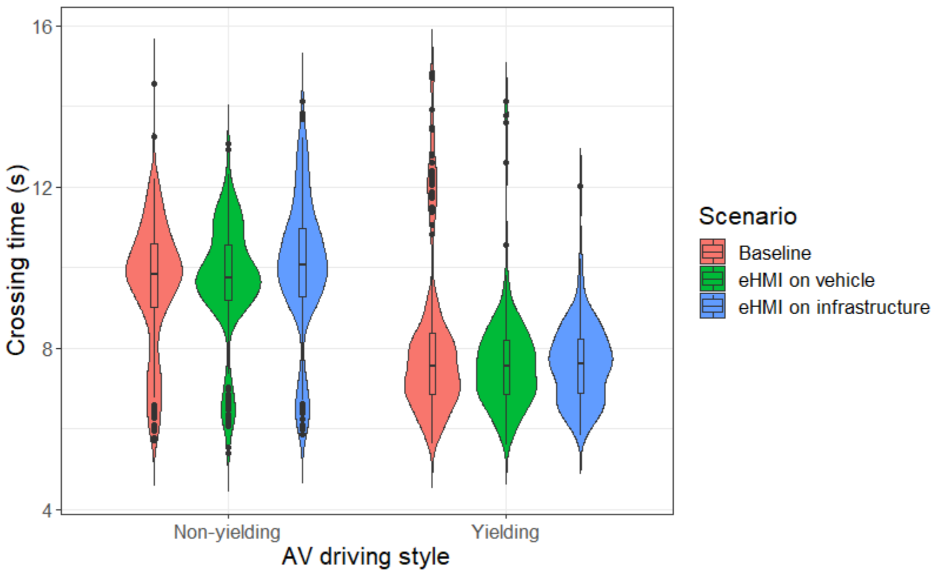


Figure 42: Box-violin plot for crossing time (s) over the scenarios and the AV driving styles. The box-violin plot contains outliers.

6.2.4 Summary

Table 11 provides an overview of scenarios in the horizontal axis and perception variables in the vertical axis. On the other hand, Table 12 represents an overview of scenario effects for behavior variables. The type of scenario variable analysed was mentioned in row 2 ("Effect

Table 11: An overview of scenario effects on perception variables. eHMI_V and eHMI_I represents eHMI on vehicle and infrastructure, respectively

Variables		Effect of scenario		
Effect studied for		eHMI_V	eHMI_I	eHMI_V
In comparison with		Baseline		eHMI_I
Perceived criticality		-	-	-
Trust		Higher	Higher	-
User acceptance	Usefulness	Higher	Higher	-
	Satisfaction	Higher	Higher	-
Emotions	Pleasure	Higher	Higher	-
	Arousal	Lower	Lower	Higher
	Dominance	-	-	-
Workload	Mental demand	Lower	-	-
	Physical demand	-	-	-
	Temporal demand	-	-	-
	Performance	-	-	-
	Frustration	-	-	-
	Effort	-	-	-
	Overall workload	-	-	-
Preference for AVs		Higher	Higher	-

Table 12: An overview of scenario effects on behavior variables. eHMI_V and eHMI_I represent eHMI on vehicle and infrastructure, respectively.

Variables		Effect of AV scenario with respect to AV driving style					
AV driving style		Non-yielding			Yielding		
Effect studied for		eHMI_V	eHMI_I	eHMI_V	eHMI_V	eHMI_I	eHMI_V
In comparison with		Baseline		eHMI_I	Baseline		eHMI_I
Pre-crossing	Approaching speed	Lower	Lower	Higher	-	-	-
	Maximum acceleration	-	-	-	-	-	-
	Maximum deceleration	-	-	-	-	-	-
	Minimum speed	-	-	-	-	-	-
	Time to maximum braking	Lower	Lower	-	-	-	-
Crossing	Crossing decision	-	-	-	Higher	Higher	-
	Critical events (from PET)	Lower	Lower	-	Lower	Lower	Higher
Post-crossing	Crossing time	-	Higher	Lower	-	-	-

studied for"), whereas the comparing scenario variable was exhibited in row 3 ("When compared with"). The scenario effects were observed for behavior variables with respect to AV driving style. From row 4, variables in columns 1 and 2 of Table 11 and Table 12 represented driver perception and driver behavior variables, respectively.

On a general scale, participants expressed higher trust, user acceptance, pleasure, arousal, and preference for AVs with eHMI than baseline. Participants were less involved in critical interactions with AVs with eHMIs than baseline. Driver compliance was higher with AVs that instruct to cross with eHMI.

6.3 Learning effects

External human machine interface is relatively a new concept for AVs on the road. In this experiment, all the participants experienced interactions with eHMI equipped AVs for the first time. Participants were likely to change their perception and behavior over multiple interactions with AVs. This could lead to a learning effect, which was studied through a correlation analysis for each driver perception and behavior variable with the interaction number (Soni, 2020). The correlations analysis was performed for each eHMI condition. No significant correlations were observed. The correlation plots and results are presented in Appendix C.

6.4 Modelling

Modelling obtains a better understanding of the combined effect of scenarios, driver characteristics, perception, and behavior variables on participant preferences, crossing time and critical events. Predicting variables were identified from the sub-research questions and conceptual framework in section 3. Participant preferences, crossing time, and critical events were the models' target (i.e., predicted) variables. In this section, the model selection criteria are explained first. Next, the model results are reported.

6.4.1 Model selection criteria

Generalized linear mixed model (GLMM) was proposed as the data were non-parametric and the experiment had a hierarchical design. Due to this design, data were repeatedly collected from the same participant. Participant responses were likely to correlate (West, 2009). To account for the hierarchical design, mixed effects were considered (Dickey et al., 2010). Mixed effects included fixed and random effects. Fixed effects were assumed to occur due to differences between participants, and random effects were assumed to occur due to within-participant differences (Garth, 2008; West, 2009).

Modelling steps included multicollinearity test, sorting data structure, identification of link distribution of target variable, identification of random and fixed effects, and model selection (Garth, 2008; Zoellick et al., 2019). First, a multicollinearity test was performed to identify the highly correlated predicting variables; where $r > 0.80$, tolerance < 0.2, and variance inflation factor (VIF) $>= 5$ (Garson, 2012; Garth, 2008). These variables lead to infinite standard errors and reduce statistical power (Garson, 2012). Hence, highly correlated predicting variables were not considered for the models. Second, the model was prepared in SPSS *version* 26.0 and R program by sorting the data structure. Participant ID and scenario order were selected as subjects and repeated measures, respectively. Third, the distribution of target variables was identified through the EasyFit app and R program. Fourth, random effects were observed through a parameter. Participant ID was included as a subject combination for the random effects. The relevant fixed effects were included in a step-wise iterative method based on lower Alkaline Information Criteria (AIC) and Bayesian Information Criteria (BIC) criteria (Zoellick et al., 2019). Finally, a model with the least AIC and BIC criteria was selected for a better fit (Oskina, 2019).

The formulation of GLMM is shown as follows:

$y_n = \beta X_n + u_n + \varepsilon_n$

where:

y_n	Preference or critical events or crossing time (predicted variable)
X_n	Vector of fixed effects (predicting variables)
β	Vector of fixed effect coefficients
u_n	Random effect parameter
ε_n	Error term
n	Observation number

6.4.2 Models

Analysis results of preference, crossing time, and critical events models are presented in this section. In addition, a list of predicting variables post multicollinearity test, target variable distribution, AIC and BIC criteria for the best-fit model are reported.

Preference model

The preference model aimed to predict which scenarios and perception variables affect preference for AVs. The model was analysed in SPSS version 26.0. Preferences were reduced to a binomial scale, where 1 and 0 represented high and low preference for an eHMI condition, respectively. Target variable (i.e., preference) link distribution was selected as binomial logit.

As shown in section 3, predicting variables for the preference model included driver characteristics and perception variables. A perception variable, satisfaction had a tolerance of 0.183 and VIF of 5.460 using the multicollinearity test (see Appendix D). Satisfaction was excluded from the predicting variables. Next, predicting variables were added for fixed effects in a stepwise forward selection procedure. This procedure was carried out for 22 model iterations before exhausting all the combinations. The final model (see Table 13 for coefficients) had the least AIC and BIC values of 621.815, and 632.544, respectively. Low preference was set as the reference category. The random effect parameter was 0.000. The fixed effects analysis (see Table 13) exhibited a significant relationship between scenarios and

Table 13: Fixed effects for high preference – GLMM. Asterisks represent significant estimates at 95%. SP represents the social preference of participants.

Model term	Coefficient	Standard error	t	P-value	95% confidence interval	
					Lower	Upper
Intercept	-3.667	0.984	-3.723	<0.001*	-5.617	-1.716
Scenario = eHMI_V	3.051	0.944	3.231	0.002*	1.181	4.920
Scenario = eHMI_I	2.609	0.948	2.752	0.007*	0.732	4.486
Scenario = Baseline	(Reference value)					
SP = Prosocial	0.225	0.541	0.416	0.678	-0.847	1.297
SP = Individualist	(Reference value)					
Usefulness	0.879	0.388	2.263	0.025*	0.110	1.648
Probability distribution: Binomial Link function: Logit						
Reference category: Low preference						
Number of observations: 44						

“high preference” for AVs. The estimates were positive (eHMI_V coefficient = 3.051, eHMI_I coefficient = 2.609), which represent a higher probability of preference for AVs. In other words, when compared to the baseline scenario, eHMI_V and eHMI_I scenarios were more likely to result in a high preference for AVs. Social preferences did not have a significant (p = 0.678) relationship with a high preference for AVs. In simple terms, AV preferences of prosocial participants were not significantly different from individualistic participants in this research. Furthermore, “usefulness” had a positive estimate (0.879), and a significant (p = 0.025) relationship with a high preference for AVs. In other terms, the perceived usefulness of a communication system has a higher probability to result in a higher preference for AVs.

Critical events model

The critical events model aims to understand the effect of predicting variables on traffic safety. From section 3.2, predicting variables contained driver characteristics, perception variables, and behavior variables in pre-crossing, and crossing stages. Among the predicting variables, driver experience (years), satisfaction, approaching speed, and minimum speed were highly correlated in the multicollinearity test (see Appendix D). These highly correlated variables were excluded from the model. Next, target variable (i.e., critical events) distribution was identified as beta distribution and the link distribution was selected as log (see Appendix D). Predicting variables were then selected for fixed effects in a forward selection process, which was carried for 24 model iterations. The final model (see Table 14 for coefficients) had the least AIC and BIC values of -345.3, and -254.4, respectively. The random effect parameter was less than 0.001.

The fixed effects analysis (see Table 14) showed a significant relationship between critical events and the eHMI_V scenario, with respect to the baseline scenario. The estimate was negative (-1.761), which represent a lower probability for critical events. In simple terms, the eHMI_V scenario had a lower probability for critical events than baseline. eHMI_I also had a negative coefficient (-0.658) but insignificantly (p = 0.273) different from baseline. Furthermore, a yielding AV had a negative coefficient (-3.870) and was significantly (p < 0.001) different to a non-yielding AV. In other terms, a yielding AV was more likely to reduce critical events than a non-yielding AV which was in line with the expectation.

Table 14: Fixed effects for critical events – GLMM. Asterisks represent significant estimates at 95%. AV_DS represents automated vehicle driving style.

Model Term	Coefficient	Standard error	t	P-value	95% confidence interval	
					Lower	Upper
Intercept	1.710	0.444	3.849	<0.001*	0.839	2.580
Scenario = eHMI_V	-1.761	0.591	-2.982	0.003*	-2.918	-0.604
Scenario = eHMI_I	-0.658	0.600	-1.097	0.273	-1.834	0.518
Scenario = Baseline	(Reference value)					
AV_DS = Yielding	-3.870	0.633	-6.114	<0.001*	-5.111	-2.630
AV_DS = Non-yielding	(Reference value)					
Probability distribution: Beta Link function: Log						
Number of observations: 244						

Crossing time model

The crossing time model predicts the combined effects of predicting variables on efficiency of the AV-HDV interactions. From section 3.2, predicting variables for the preference model included driver characteristics, perception variables, and behavior variables in pre-crossing and crossing stages. Among these variables, driver experience (years), satisfaction, approaching speed, minimum speed, crossing decision, and critical events were highly correlated in the multicollinearity test (see Appendix D). Thus, these predicting variables were excluded. Target variable (i.e., preference) distribution was identified as gamma distribution and the link function was log (see Appendix D). Predicting variables were then selected from 28 model iterations. The best-fit model (see Table 15 for coefficients) had the AIC and BIC values of -315.669, and -301.952, respectively. The random effect parameter was 0.005.

The model results (see Table 15) illustrated that the eHMIs did not have a significant effect on the crossing time compared to baseline. Crossing time did not have a stronger relationship (|coefficients| < 0.5) with the model terms (see Table 15). Among the model terms, perception variables such as usefulness and arousal had a negative coefficient (-0.019 and -0.018, respectively) and also a significant ($p = 0.044$ and $p < 0.001$, respectively) relationship with the crossing time. In other terms, perceived usefulness and arousal were found to decrease the crossing time. Among the pre-crossing behavior variables, maximum deceleration had -0.032 coefficient and significant ($p < 0.001$) relationship with the crossing time. An implication, maximum deceleration was likely to reduce the crossing time. However, maximum acceleration had no significant ($p = 0.163$) relationship. On the other hand, the yielding style had a negative coefficient (-0.144) and significant ($p < 0.001$) effect on the crossing time when compared to the non-yielding driving style of AV. A non-yielding AV was not likely to increase the crossing time than a yielding AV.

Table 15: Fixed effects for crossing time – GLMM. Asterisks represent significant estimates at 95%. AV_DS represents automated vehicle driving style.

Model Term	Coefficient	Standard error	t	P-value	95% confidence interval	
					Lower	Upper
Intercept	2.126	0.0414	51.381	<0.001*	2.045	2.208
AV_DS = Yielding	-0.144	0.0275	-5.236	<0.001*	-0.198	-0.090
AV_DS = Non-yielding	(Reference value)					
Usefulness	-0.019	0.0095	-2.023	0.044*	-0.038	-0.001
Arousal	-0.018	0.0046	-3.856	<0.001*	-0.027	-0.009
Maximum acceleration	0.013	0.0091	1.400	0.163	-0.005	0.031
Maximum deceleration	-0.032	0.0048	-6.604	<0.001*	-0.041	-0.022
Probability distribution: Gamma Link function: Log						
Number of observations: 244						

6.4.3 Summary

The modeling results are summarized in Table 16. Each column represents a model with its significant variables. eHMI_V and eHMI_I were found to have a significantly greater effect on driver preference for AVs when compared to baseline. Among the perception variables, usefulness had a positive impact on preference for AVs. The critical events model explained that eHMI_V a yielding AV had a lower effect when compared to baseline condition and non-yielding AV, respectively. The crossing time model predicted that usefulness, arousal and maximum deceleration variables were less likely to affect the crossing time of participants. A non-yielding AV had a major impact on crossing time than a yielding AV.

Table 16: An overview of GLMM results. eHMI_V and eHMI_I represent eHMI on vehicle and infrastructure, respectively. '+' or '-' show a significantly positive or negative effect of a variable on the model, respectively. '>' or '<' explains a greater or lower effect of a scenario in comparison to others, respectively.

Preference for AVs	Critical events	Crossing time
eHMI_V > Baseline eHMI_I > Baseline + Usefulness	eHMI_V < Baseline Yielding < Non-yielding	Yielding < Non-yielding - Usefulness - Arousal - Maximum deceleration

7 Discussion and conclusion

This section discusses the study overview, answers to sub-research questions, and reflects on the findings and method. Further, the section provides conclusions and limitations of this research.

7.1 Research overview

Automated vehicles are expected to arrive in the next few decades on our road network, where AVs will interact with HDVs (Bansal & Kockelman, 2017; Southfield, 2016). During these interactions, the human role differs in interactions with AVs (Vinkhuyzen & Cefkin, 2016). Human drivers and AVs use different forms of communication, and their interaction could lead to a communication void on road. In order to fill the void, this research explores the potential of eHMIs for AVs' communicative interactions with HDVs.

The research scope was to understand the effect of eHMIs on the communicative interactions with AVs at unsignalized T-intersections. In this study, communicative interactions referred to the use of communication signals by AV to negotiate the right-of-way with an HDV at the intersection. Communicative interactions were measured with driver perception and behavior variables. In order to study these variables, participants drove in a simulator and answered questionnaires on their experiences with eHMIs. The eHMI conditions included baseline and eHMIs that differed with their placement. The eHMI was either placed on vehicles or road infrastructure. The experimental data in all the scenarios were compared to understand the scenario effects on driver perception and behavior.

By studying the eHMI effects in the driving domain, this study filled a literature gap on AV interactions with different road users. Understanding the placement effect of eHMIs provided a step to identify the responsible authorities (e.g., road authority and AV manufacturer) for constructing and maintaining eHMIs. This research measured driver perception and behavior that provided a detailed view of driver interactions with AVs. In this research, the preference model identified the factors that improve social acceptance of AVs. Furthermore, this research used models to predict and estimate the impact of eHMIs on traffic safety and efficiency of the AV-HDV interactions. Based on eHMI implications for traffic safety and efficiency of the interactions, recommendations were provided to road authorities, AV manufacturers, and policymakers for better infrastructure design, AVs, and new policies.

7.2 Answers to sub-research questions

The main research question (see section 3.3) could be answered through sub-research questions. This sub-section aims to answer the sub-research questions using the analysis results from section 6.

Sub-question 1: *What are the effects of eHMI conditions on driver perception?*

The impact of each eHMI condition on driver perception variables were studied and the impacts were compared between the different eHMI conditions (i.e., baseline, eHMI on vehicle and eHMI on infrastructure).

The analysis of driver perception variables revealed significant differences among the three conditions in the user acceptance, trust, emotions, and workload. When compared with baseline (i.e., no eHMI) condition, participants expressed higher user acceptance and trust in AVs with eHMIs (i.e., eHMI on vehicle or infrastructure). Participants felt more pleasant and calmer in the interactions that included eHMIs. Among the two eHMIs, participants felt calmer with eHMI on infrastructure than on the vehicle. Participants reported significantly lower mental demand in the scenarios with eHMI on the vehicle than baseline condition. Furthermore, drivers preferred AVs with eHMIs. These observations were in line with hypothesis 1 as the eHMIs improved driver perception, in terms of user acceptance, trust, pleasure, calmness and mental demand, during the interactions with AV.

Sub-question 2: *What are the effects of eHMI conditions on driver behavior with respect to AV driving style?*

In order to gain insights on driver behavior, each behavior variable was analysed for differences among the scenarios in section 6.2. The analysis was carried separately for each driving style of AV.

Non-yielding AV: Among the behavioral variables in the pre-crossing stage, approaching speed and time to maximum braking were significantly different among the eHMI conditions. In comparison with baseline condition, participants approached the intersection with lower speed when AV signals to yield through eHMIs. Participants maintained a lower approaching speed with the eHMI on infrastructure than eHMI on the vehicle. When AV signals the participants to yield, they took less time to reach maximum baking with eHMIs than baseline condition. This observation indicated that participants brake early to yield the right-of-way for the AVs that use eHMIs.

Among the behavioral variables in the crossing and post-crossing stages, critical events, measured by Post-Encroachment Time, and crossing time had significant differences among the eHMI conditions. Participants had lower critical interactions with non-yielding AVs that communicate with eHMIs compared to AVs without eHMI. Crossing time was measured from the moment when HDV triggered the AV and its signals to the moment when HDV took the right turn and exited the intersection. Participants took less time to cross with eHMI on infrastructure than the other two conditions.

Yielding AV: Participants had differences in the behavioral variables of crossing stage across the three conditions. Participants showed higher compliance with eHMIs than with the baseline condition, which was partly in line with hypothesis 2. However, participants' compliance did not significantly differ between the two eHMIs. Participants had fewer critical interactions with yielding AVs that communicate via eHMIs when compared with the baseline condition. Specifically, participants had fewer critical interactions with AVs that convey intent with eHMI on infrastructure.

Sub-question 3: *Which factors related to eHMI conditions, driver characteristics and perception influence driver preference for AVs?*

A preference model was developed to predict the social acceptance of AVs. eHMIs were probable to improve participant preference for AVs, as expected in hypothesis 3. More specifically, eHMI on vehicle has a positive and higher effect size than the other conditions. Furthermore, preference was likely to increase when participants perceived an AV communication system to be useful. However, none of the driver characteristics had a significant effect on the preference for AVs.

Sub-question 4: *Which factors related to AV and driver characteristics, perception, and pre-crossing behavior influence the critical events during right turn maneuver?*

A critical events model was developed to understand the implications for traffic safety during right-turn maneuvers. In comparison to the baseline condition, eHMI on the vehicle was found to reduce the critical interactions between the participants and AVs. This result was in line with hypothesis 4 as the participants knew the AV intent and speed with eHMI on vehicle. However, the critical interactions did not seem to differ with eHMI on infrastructure and baseline condition. Furthermore, yielding AVs were probable to reduce the critical interactions with participants than non-yielding AVs. The driver characteristics and pre-crossing behavior have no significant impact on the model output.

Sub-question 5: *What is the effect of AV characteristics, driver characteristics, perception, pre-crossing and crossing behavior on the time drivers take to complete right turn maneuver?*

AV-HDV interaction efficiency implications were predicted with a crossing time model for right-turn maneuvers. None of the eHMIs probably influenced the time to cross the intersection when compared with the baseline condition. This was not in compliance with hypothesis 5 as the eHMI on infrastructure did not convey AV speed to the human driver. Furthermore, the driver characteristics were found not to affect the crossing time. A non-yielding AV was more likely to increase the participants' time to cross the intersection than a yielding AV. Participants perceived usefulness of communication system was not found to increase the time to cross. On similar lines, participant excitement level and maximum deceleration were not found to increase the participants' time to cross the intersection.

7.3 Discussion

The principal purpose of this research is to understand the effect of AVs' eHMIs on human driver interactions, where eHMIs differ in placement. This research, however, makes an assumption that AV driving style is similar to HDV. This research studies the AV-HDV interactions at unsignalized T-intersections.

The key findings of this study are as follows. eHMIs have a significant effect on driver perception and behavior in the interaction with AVs. In interactions with eHMIs, drivers express significantly higher trust, user acceptance, pleasant and calmer experiences. In particular, eHMI on vehicle reduces mental demand and eHMI on infrastructure improves calmness of drivers. The effect of eHMIs on driver behavior is significantly higher in the interactions with uncertainty. Drivers break early and are less likely to involve in critical interactions with AVs that communicate with eHMIs. In particular, eHMI on vehicle is found to reduce the critical interactions between AVs and HDVs. Drivers also show compliance with AVs that signal to cross with eHMIs. These observations are consistent with the previous studies on eHMIs.

This sub-section provides a scientific and critical reflection on the method and findings of the research. First, the section critically evaluates and discusses the results with support from the literature. Next, the section discusses the implications of the method on results.

7.3.1 Reflection on findings

This sub-section discusses and evaluates the research findings with the literature. In order to understand the effect of AV eHMIs on communicative interactions with HDVs, driver perception and behavior results are discussed.

Perception: eHMIs influence driver perception in a positive direction. Among the perception variables, drivers express higher user acceptance and trust on AVs with eHMIs. An explanation is that drivers want to receive information on AV intent for decision-making. In addition, drivers find it easier to learn eHMI signals and useful for future interactions. On similar lines, Avsar et al. (2021) and Rettenmaier et al. (2020) discussed that drivers find the eHMI signals as simple to learn and beneficial for decision-making in bottleneck situations such as T-intersections and narrow roads, respectively. In our study, the trust and user acceptance do not differ significantly between eHMI on vehicle and infrastructure. This result suggests that the eHMI placement does not affect user acceptance and trust in AVs at intersections.

For eHMI conditions, drivers experience the interactions with AVs as pleasant and calm. This result implies that drivers are relaxed to explicitly know the AV intent. This result is supported with the post-experiment interview, where few drivers mentioned that they made decisions with confidence in the scenarios with eHMI. This observation was reflected in Habibovic et al. (2018), where the pedestrians felt better to know the AV intent with eHMIs. These observations explain that explicit information helps the road user to understand AV intent clearly and make decisions with certainty. In addition, our results suggest that drivers feel calmer when the eHMI design is inspired by traditional road infrastructure (e.g., traffic signal). This suggestion was observed when the drivers expressed a lower arousal score with eHMI on infrastructure than on the vehicle.

Perceived criticality of the interactions did not differ significantly between baseline and eHMI conditions. On contradictory terms, Avsar et al. (2021) observed that drivers perceived AV interactions as significantly safer with eHMI. A possible reason for the difference is that HDV-drivers experience an interaction as critical based on a possible collision course with AV. HDVs in Avsar et al. (2021) follow a different collision course when compared to our research. The authors instructed drivers to start from a stand-still position before crossing at the intersection. Our study allows the driver to approach the intersection at their desired speed.

eHMI on vehicles reduces the mental demand of drivers in the interactions when compared to baseline. An explanation is that driver receives more information from AV, namely intent and vehicle behavior, when eHMI is on the vehicle. This observation was underpinned from the interviews, where a few drivers explained that they know the AV intent and speed when they look at an AV with eHMI on top. However, mental demand with eHMI on infrastructure was not found to significantly differ from baseline. A reason is that the eHMI on infrastructure and AV are in different lines of driver vision. During the interview, some drivers mentioned that they looked in two different directions to know AV intent. These observations suggest that the placement of eHMI affects the mental demand of the driver.

Preference model predicts that drivers are likely to prefer AVs with eHMIs over baseline conditions. In addition, the perceived usefulness of an AV communication system (e.g., eHMI) affects the driver preference for AVs. These results suggest that AVs with eHMIs, which are perceived beneficial, have the potential to raise social acceptance of AVs. This suggestion is in line with Vinkhuyzen & Cefkin (2016), who illustrated that eHMIs could lead to the development of socially acceptable AVs. However, social acceptance of AVs among human drivers is likely to remain unaffected with eHMI placement. This is observed when the driver preferences do not differ significantly with different eHMI placement.

Behavior: The effect of eHMIs on driver behavior differs with AV driving style. During the HDV interactions with non-yielding AVs, behavior variables in the pre-, mid- and post-crossing stage, such as approaching speed, time to maximum braking, critical events and crossing time, have significant differences. However, none of the behavior variables has significant differences in the pre- and post-crossing stage for the yielding AVs with eHMIs. An explanation is that eHMIs are beneficial in uncertain interactions that need negotiations. This explanation was also reflected in on-road studies as mentioned by Habibovic et al. (2019). This could also be due to the positive effect of eHMIs on driver emotions, trust and user acceptance.

Non-yielding AVs: Significant differences are identified in variables across different crossing stages. Drivers have lower approaching speed and time to maximum braking with eHMIs than baseline conditions. Probable critical events are lower with eHMIs. These results explain that drivers brake early, approach the intersection with lower speed and reduce critical interactions for eHMI conditions. These observations suggest an improvement in driver performance with eHMIs, which is in line with other studies (Clercq et al., 2019; Rettenmaier et al., 2020; Winter & Dodou, 2021). Clercq et al. (2019), and Winter & Dodou (2021) explained that the safety performance of other road users increases with eHMIs in the pedestrian-AV interactions.

Rettenmaier et al. (2020) observed a reduction in narrow-road crashes in the AV-HDV interactions with eHMIs.

For non-yielding AVs, lower approaching speed is observed with eHMI on infrastructure than on the vehicle. This is also reflected in the crossing time. Drivers took more crossing time with eHMI on infrastructure. This could be that eHMI on infrastructure, which is inspired by a traffic signal and provides calmer experience to human drivers, persuades the driver to reduce the approaching speed when eHMI signals yield. Another possible reason is that eHMI on infrastructure is in the driver's line of sight, whereas eHMI on the vehicle is not in the line of vision.

Yielding AVs: Significant differences are observed in crossing stage variables, namely crossing decision and critical events. More drivers cross the intersection before the AV with eHMIs than AV without eHMI. Probable critical events are lower with eHMIs. These results suggest that eHMIs have the potential to affect driver decision to cross before AVs, safely. On similar lines, Avsar et al. (2021) observed that eHMIs and AV driving styles influence driver decision to cross safely and accept lower gaps at T-intersection. A study on pedestrian-AV interactions by Clercq et al. (2019) show that road users feel safer to cross before AV when it signals to cross.

Traffic safety and interaction efficiency implications: Critical events and crossing time models are developed to understand the combined effects (e.g., AV driving style, eHMIs, driver perception) on traffic safety and interaction efficiency. The critical events model explains that a yielding driving style and eHMI on the vehicle are likely to reduce the critical interactions at the intersections. This could be due to lower mental demand with eHMI on vehicle compared to baseline. The model suggests that traffic safety is achieved when AV is yielding and signals to cross with an eHMI on the vehicle when compared to a non-yielding AV with no eHMI.

The crossing model explains that a yielding driving style of AV, perceived usefulness of AV communication system, driver arousal and maximum deceleration are found not to increase the crossing time. The model also suggests that the eHMIs have no implications for interaction efficiency through crossing time. Efficiency of AV-HDV interactions could be understood from driver compliance at the intersections. Our study exhibits that eHMIs improve driver compliance when AV is yielding, suggesting that eHMIs have the potential to improve the efficiency of AV-HDV interactions, at the T-intersection. In line with Avsar et al. (2021), who observed that drivers accept smaller gaps with eHMIs, which has positive implications for efficiency at the intersections.

7.3.2 Reflection on method

This sub-section provides a critical view of the driving simulator method. The assessment of methodology reflects on the effect of design choices on results.

The experimental layout, in this research, consisted of distributor roads with a speed limit of 80 kmph. Other road types exist based on different speeds. Interactions between vehicles can occur on high-speed roads such as motorways, where drivers have less time to perceive and act (Risto et al., 2017). This may influence the road users to rely more on implicit signals than explicit signals such as eHMIs. eHMI effects on driver perception and behavior are expected to be less prominent on high-speed roads.

This research experiment involved participants performing right turns at unsignalised T-intersections. However, different types of maneuvers (e.g., merging, turning left) and road layouts (e.g., X-intersection, shared space) exist. Different road conditions could lead to different driving behavior (Soni, 2020). The results of this research, hence, require validation with relevant studies on other road conditions.

During the experiment, participants had minimum interaction with other road users. For instance, vehicles in the opposite lane of AV disappear on participants reaching the intersection to reduce mental workload. However, other vehicles or vulnerable road users interact with HDVs in mixed traffic environments on road. In such complex interactions, the scalability and resolution of eHMIs are expected to affect driver decisions (Dey et al., 2020). This could lead to more significant differences in driver perception and behavior between eHMI on vehicles and infrastructure.

To make the participants interact with AV at the intersection, the participants were instructed to arrive at the trigger location (see Figure 19) with 50 kmph. However, on-road HDVs are likely to arrive at the intersections with different deceleration rates and speeds (El-Shawarby et al., 2007). eHMIs are expected to affect the deceleration rates of HDVs when approaching the intersection on road.

The weather in the driving simulator experiment was set to be clear and no objects obstruct the participant view of the intersection. AVs and their intentions were clearly visible to the participants when they reach 70 m from the intersection, as suggested by CROW (2012). These design choices increase the recognizability of AV intent through eHMIs. However, visibility, in reality, is affected by several external factors such as weather, buildings, and trees. These factors are likely to obstruct the visibility of eHMIs. Participant compliance with AVs is expected to reduce with eHMIs in sub-optimal conditions.

Two novel eHMI concepts were designed in this research. Both eHMIs convey AV intent through light displays. However, Dey et al. (2020) explained that different forms (e.g., text, speech, display) and colour formats (e.g., red, cyan, purple) could be used to convey AV intent. The design of eHMIs has the potential to affect driver interactions. If AV conveys intent through text, participants might find it difficult to interpret the message from a farther distance and might distract them from the task of driving. In such situations, participants do not rely on eHMIs which are unlikely to increase trust and user acceptance.

7.4 Conclusion

The main research question is answered with the observations from sub-questions. The main research question is:

What is the effect of eHMIs on AVs' communicative interaction with human drivers who perform a right-turn maneuver at unsignalized T-intersections?

Communicative interactions are measured in driver perception and behavior at the T-intersections.

Among the driver perception variables, drivers experience pleasure and calmness in the interactions with AVs that signal with eHMIs. In particular, eHMI on vehicles reduces the mental demand, and eHMI on infrastructure increases the calmness experience of the drivers. Drivers expressed higher user acceptance and trust in AVs with eHMIs. As the eHMIs have a positive effect on driver perception, the preference model predicts that drivers choose AVs with eHMIs over no eHMI. These observations imply that eHMIs are likely to improve social acceptance of AVs at T-intersections.

The effect of eHMIs on driver behavior differs with AV driving style. The eHMIs have a significant effect on the crossing stage variables for yielding AVs. Whereas in interactions with non-yielding AVs, eHMIs have a significant effect on behavior variables in the pre-crossing, crossing, and post-crossing stages. These observations suggest that the effect of eHMIs is significant on driver behavior in interactions with higher uncertainty. Drivers brake early and approach the intersection with lower speed to prevent critical interactions with non-yielding

AVs that communicate intent through eHMIs. Specifically, among the eHMIs, eHMI on infrastructure reduces the approaching speed and increases the crossing time of HDVs. For yielding AVs, drivers are less involved in critical interactions with AVs that signal with eHMIs than baseline.

eHMI on the vehicle is found to reduce critical interactions between HDVs and AVs compared to no eHMI condition. However, this finding was not reflected for the eHMI on infrastructure based on the critical events model. These observations imply that eHMI on the vehicle has positive implications for traffic safety at the T-intersections. Though the crossing time model does not provide implications of eHMIs on the interaction efficiency, drivers' crossing decisions could provide a sense of the driver compliance. As drivers cross before AVs, driver compliance is higher when AVs yield and send eHMI signals to HDVs. Hence, eHMIs improve driver compliance that can positively affect the efficiency of AV-HDV interactions at the T-intersection.

In conclusion, eHMIs have a positive impact on AVs' communicative interactions with HDVs at T-intersections. In particular, eHMI on vehicle can reduce the critical interactions between AVs and HDVs at T-intersections. No significant differences were observed between the eHMI conditions for the acceptance of AVs and interaction efficiency.

7.5 Limitations

In order to provide insights for future research, the limitations of this research are discussed. Some limitations were explained in section 7.3.2. The other limitations were:

- A high proportion of participants had at least a bachelor's degree in science. These participants have experience with ADAS systems and they might understand the eHMI concepts quickly and clearly. Hence, the findings are valid for a similar population group only.
- This research focuses on eHMIs that communicate the AV intent correctly. There could be interactions where the eHMIs miscommunicate AV intent to HDVs due to system malfunction. Rettenmaier et al. (2020) observed that eHMI miscommunication reduces user acceptance and trust in AVs. The study on eHMI miscommunication is out of this research scope.
- This research involves two driving styles of AVs, namely yielding and non-yielding. Some studies (Ackermann et al., 2019; Imbsweiler et al., 2018; Uttley et al., 2020) explain that vehicle driving style differs with acceleration and deceleration rates that have a significant impact on driver behavior. However, the effects of different AV movements and eHMIs were not studied on driver interactions in this research.
- The application of the right-hand rule (i.e., yielding to vehicles on right) differs with the culture and context on road. The non-yielding AVs do not follow the right-hand rule in this research. Few participants expressed that the non-yielding AVs influence their perceived criticality of the interactions. This research did not observe driver perception with respect to AV driving style.
- Steering wheel data is required to understand the lane deviation behavior of the vehicle. The 'Fanatec wheelbase' steering wheel of the driving simulator does not support power steering. Few participants oversteer while crossing at the intersection. Hence, this research did not analyse the lane deviation behavior of HDVs.

8 Recommendations

This section presents recommendations to various stakeholders (e.g., road authorities, AV manufacturers, policymakers) that aim to improve and implement AV technology for the betterment of society. This section also suggests research areas for future studies.

8.1 Recommendations for future research

Previous studies (e.g., Clercq et al., 2019; Eisma et al., 2020; Winter & Dodou, 2021) explain a performance improvement for pedestrian-AV interactions with eHMIs. On similar lines, our findings show an improvement in human driver performance and on-road safety with eHMIs. Future experimental investigations, therefore, are required to understand the potential of eHMI for interactions with multiple road users such as pedestrians, human drivers, cyclists, and AVs.

Our findings show that the preference for AVs and interaction efficiency are not significantly different between the eHMI on vehicle and infrastructure at T-intersections. Future research is recommended to explore the two eHMI concepts in different on-road interactions (e.g., merging on highways, narrow roads, X-intersections).

Novel eHMI concepts are created in this research to communicate AV intent with higher resolution and scalability on roads. Future research could adapt and implement the novel eHMI concepts for interactions in a mixed traffic environment with multiple road users. Besides different road users, the mixed traffic environments differ with penetration rates and platooning of AVs. eHMI with higher scalability could inform the platoon intent to other road users. For instance, a leader AV can use an eHMI to communicate the intent of a platoon of 10 follower AVs. If the driver is informed with the intent of the AV platoon using eHMIs, further studies could assess if the traffic efficiency improves with intent communication in AV-HDV platoon interactions.

Previous research (e.g., Schoenmakers et al., 2021; Soni, 2020; D. Yang et al., 2019) observed that human drivers adapt their behavior in interactions with AVs. Our study does not explore the behavioral adaptation with eHMIs in the long-term application. As the human drivers know the AV intention with eHMI, they might drive closer to the AVs that leads to critical interactions. Further research is required to determine whether the long-term application of eHMIs have negative implications for traffic safety in mixed-traffic environment.

Our study implements GLMM models to understand the combined effect of driver characteristics, perception and eHMI conditions on behavior variables that influence traffic safety and efficiency of the interactions. The behavior variables in our study do not facilitate understanding the implication on traffic efficiency at a vehicle trajectory level. Further work needs to implement other modelling techniques, such as machine learning models and microsimulation models, and micro-simulation packages (e.g., Simulation of Urban Mobility) to generate driver trajectories, and understand the impact of eHMIs on traffic efficiency at a finer level.

Our research provides findings and qualitative, and quantitative datasets that could be used to validate future research and better understand the eHMI effects on human-driver interactions in different driving conditions.

8.2 Recommendations for transportation specialists

The models in this study explore the human factors and the relation between human driver cognition and behavior in the interactions with AVs. In addition, the driver behavior is studied at different crossing stages which provide a deeper insight into driver decisions at T-intersections. The transportation specialists could widen the applicability of their simulation models with the inclusion of human factors, perception and behavior insights from this research. However, inclusion of all the human factors, perception and behavior variables might lead to overfitting and complexity of models. Further research is required to investigate the relevant variables that improve clarity and prediction power of simulation models.

Further analysis is needed to explore the relation between the driver perception (e.g., trust, perceived criticality, emotions) and behavior variables (e.g., approaching speed, post encroachment time, crossing time). For instance, a GLMM model could identify the human factors that have a significant effect on the driver behavior. In this research, GLMM shows that the usefulness of AV's communication system and driver arousal have an effect on crossing time. Transportation specialists need to explore such models to better understand the reason behind the driver actions. The experimental data from this research could be used by the transportation specialists for further analysis.

Our study observed that AVs with eHMI influence the driver behavior. However, current simulation models do not include the change in human driver behavior with AV communication type (e.g., no eHMI, eHMI on vehicle or infrastructure). Future simulation models might need to consider the eHMI effects for mixed traffic environment. In order to consider the eHMI effects, transportation specialists could include an attribute for the driver behavior that differs with the presence or type of an eHMI for the AV.

8.3 Recommendations for AV manufacturers

Our research studies a novel (directional) eHMI concept placed on the vehicle in the mixed-traffic environment. This eHMI design could contribute to scalability and higher resolution through a clear communication with other road users. Hence, AV manufacturers are recommended to further investigate and optimise the design of the directional eHMI to make it suitable for different on-road interactions.

The preference model predicts the effect of eHMI conditions and driver perception on social acceptance of AVs. In order to improve the acceptance, AV manufacturers can exploit and better understand the predicting factors. In this research, the preference model exhibits that the social acceptance of AVs is influenced by predicting factors, such as eHMIs and perceived usefulness of the communication system. AV manufacturers are recommended to consider the mentioned predicting variables (from this research) in the AV design to test and develop socially acceptable AVs.

AV manufacturers are recommended to consider the traffic rules while designing the eHMIs. eHMIs need to supplement the traffic rules but not redefine it. If not, uncertainty and unsafety on roads could increase. As the eHMI on vehicle is a novel concept, drivers of higher age groups expressed trouble adapting to the eHMI in our study. AV manufacturers are suggested to develop simple eHMIs with a goal to minimise the learning effects across all the socio-demographics.

8.4 Recommendations for the road authority

Road authorities are expected to face challenges to implement the eHMI on roads. The recommendations are provided to handle three challenges, namely technical, legal and acceptance. The challenges were briefed by a senior consultant from CROW.

Recommendations for the technical challenges: A technical challenge lies in standardizing eHMIs. Road authorities are recommended to collaborate with AV manufacturers in developing industry standards for eHMIs. For instance, such collaboration could aim at standardizing the modality and nature of the message (i.e., eHMI signal) that is effective and acceptable among the road users. Another difficulty stems from synchronizing the eHMI with the current road infrastructure (e.g., traffic lights). The road authority and AV manufacturer collaboration is suggested to explore the hardware communication systems that effectively transmit eHMI information between AV and the smart infrastructure. As the traffic light design provided calmness to the participants, road authorities could explore the methods for successful integration of eHMIs in advanced traffic controllers (e.g., intelligent traffic light installations).

Recommendations for the legal challenges: A challenge exists with the liability of crashes between AVs and HDVs. This could occur when the eHMI signal does not accurately inform to the human driver. Before the installation of eHMIs, a failure analysis could distinguish the liabilities of the involved parties (e.g., road authorities and AV manufacturers). Another recommendation is to develop failsafe plans to prevent crashes in the first place. For instance, eHMI remains inactive to prevent miscommunication when there are network latency issues. Another challenge lies in data security and privacy of AV messages. Road authorities could assign an anonymous ID for each AV message. These IDs need to regenerate for every fixed time period.

Recommendations for the acceptance challenges: The difficulty arises when the human drivers do not show the trust and acceptance for AVs despite their benefits. This difficulty could increase critical interactions in mixed-traffic environment. Our research explored two eHMI concepts that could improve driver trust and acceptance of AVs. The participants preferred AVs with eHMIs as the design was simple and intuitive. Hence, road authorities are recommended to further explore the eHMI designs that are simple, intuitive and acceptable among the road users. Higher acceptance in the society could boost the largescale development and application of eHMIs on the road.

8.5 Recommendations for policymakers

Our findings show that eHMIs could reduce driver workload and positively affect driver emotions. Modelling results illustrate that the eHMI on vehicle has the potential to reduce critical events at T-intersections, which benefits society. Policymakers are recommended to carry out a cost-benefit analysis to quantify the eHMI effects for society at large. In addition, policymakers are recommended to introduce policies that improve the AV communication with human road users. For instance, the policymakers could provide grants to the collaboration of AV manufacturers, road authorities and research institutes that explore simple and intuitive eHMIs to communicate AV intention with human drivers.

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Appendices

Appendix A: A thesis in six posts

This appendix illustrates the master thesis in six social-media (Facebook) posts to provide a quick thesis overview with a backdrop of memes for a fun and informal setting.

Nischal is at TU Delft

April 1, 2021 ·

#ThesisUpdate1

Hi, I am Nischal, the author of this thesis. The #AimofMyThesis is to explore interfaces that help automated vehicles to communicate their intent with human-driven vehicles, effectively.

Follow my posts (with memes) to get an overview of my thesis journey😄

#HDVs #AVs #Communication #TrafficPsychology

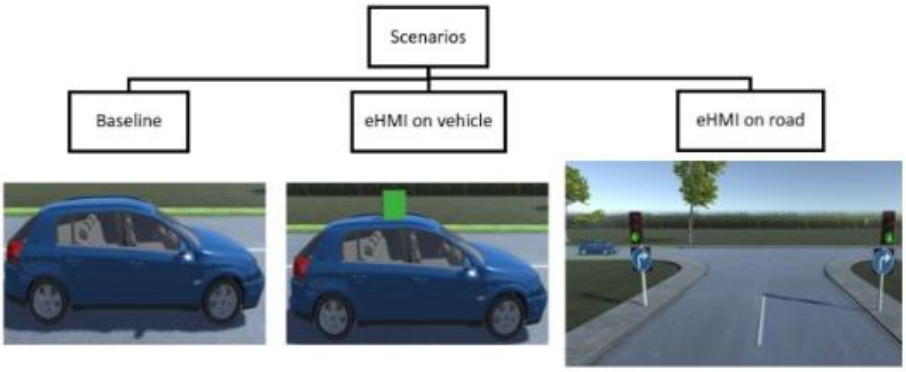
Nischal is at TU Delft
May 20, 2021 ·

#ThesisUpdate2
I studied the literature on communication among human drivers, pedestrians and automated vehicles in the interactions. Literature explains that automated vehicles can express intent with #ExternalHumanMachineInterface(eHMI). However, the literature is divided on eHMI recommendations for automated vehicles.

#Confusion #AfterReview

Nischal is at TU Delft
June 20, 2021 ·

#ThesisUpdate3
I developed two eHMIs for automated vehicles to test in the interactions with human drivers. The eHMI is either placed on vehicle or road. eHMI on vehicle is like a cube and eHMI on infrastructure is like a traffic signal. The scenarios in my thesis differ with the eHMI conditions.



Nischal is at TU Delft

July 28, 2021 ·

#ThesisUpdate4
A driving simulator experiment was conducted with 46 participants. In each scenario, participants drive to the intersection where they interact with AVs that communicate with eHMIs. Participants filled a questionnaire on their experiences after each scenario. At the end of experiment, participants expressed their preference for eHMIs.
Sometimes, the simulator had issues in running the experiment. Thank you to the participants who were patient and provided support.

#DrivingSimulator #SupportingResearch

Nischal is at TU Delft

September 28, 2021 ·

#ThesisUpdate5
The results show that eHMIs have a clear and positive effect on driver emotions, user acceptance and trust on AVs. More than 95% of participants preferred at least one type of eHMI. However, participants are divided on their preference within the type of eHMI (i.e., eHMI on vehicle vs eHMI on road).
Furthermore, participants showed more compliance with AVs' explicit intent.
Modelling results elaborate that eHMI on vehicle is less likely to increase critical interactions with AVs than baseline.

#Results #DriverPerception #DriverBehavior

Nischal is at TU Delft
October 25, 2021 ·

#ThesisUpdate6

#Conclusion (1/3)
eHMIs enhance traffic efficiency and social acceptance of AVs on road.

#Conclusion (2/3)
eHMI on vehicle is likely to reduce critical interactions between automated vehicles and human driven vehicles.

#Conclusion (3/3)
Hence, eHMIs improve AV communication with human drivers on road.

Thank you for your attention!

#SocialAcceptanceofAVs #TrafficSafety #Traffic Efficiency
#AVManufacturers #RoadAuthority

Appendix B: Questionnaires

B.1 Recruitment Questionnaire

Opening statement

You are being invited to participate in research to understand the interactions between human drivers and automated vehicles. This is a master thesis project which is being done by Shiva Nischal Lingam. The project is supported by the Delft University of Technology and Royal HaskoningDHV. The project is approved by the Human Research Ethics Committee (HREC), TU Delft.

This research involves two phases. Initially, you are requested to answer the questionnaire on details such as name, email address, gender, profession, driving experience, social preferences, and initial trust in automated vehicles. This will take you around 10 minutes to complete. Then you are selected for the second phase, based on your responses. You are contacted using your email address. The second phase involves a driving simulator experiment, where you are asked to drive in a driving simulator and answer questions on your driving experience. The experiment will take you around 60 minutes to complete.

The driving simulator experiment is planned to conduct at CiTG, TU Delft from the 2nd week to 4th week of July between 08:00 – 17:00. You can book a timeslot based on your availability. You will receive an email that details more information about the experiment once you submit this questionnaire.

Your participation is completely voluntary and you have the right to withdraw at any moment. You are free not to answer any question. I encourage you to participate in both phases of research because both of them are necessary in completing the research. On successful completion of the experiment, you receive a reward worth of €10 euros (from bol.com) as a kind gesture.

Risks and safety: We believe that there are no major risks associated with this research study. However, some of the participants might experience minor nausea while driving in the simulator. To minimise nausea, the driving scenarios are designed for shorter duration. If you experience discomfort, you can withdraw from the experiment at any instance.

Strict approved measures are followed to ensure the safety of participants and researcher and minimise the risk of spreading coronavirus. The social distancing of 1.5 meters will be maintained throughout the experiment. You are asked to wear gloves before driving the simulator. All the study equipment will be sanitized after every participant use. In accordance with RVIM-guidelines for COVID-19, we request you not to travel via public transport for the experiment. Please do not travel to the experiment if you have COVID-19 symptoms.

Data storage and confidentiality: We will safely store the data in a secured research repository called Project Storage at TU Delft. The data is regarded as confidential and it will not be shared will external users beyond study group researchers. A month after the end of experiment, the data from both phases is anonymized and personal data such as name and email addresses will be deleted from the database. If you need information on your data, please contact the researcher within a month after the experiment. After this period, we cannot trace back and provide you the data as the processed data will not have your personal information. The processed data will be used to generate observations that might be published in the academic proceedings. The processed data will be shared on 4TU.Research for future research purposes.

If you have any questions, feel free to contact us.

Shiva Nischal Lingam

S.N.LINGAM@student.tudelft.nl

Dr. ir. Haneen Farah

h.farah@tudelft.nl

Ir. Anastasia Tsapi

anastasia.tsapi@rhdhv.com

1. By clicking the button below, you acknowledge:
    a. Your participation is voluntary
    b. You are more than or equal to 18 years of age
    c. You have a valid driving license (from any country)
    d. You have at least 3 years of driving experience

2. You are aware that you can choose to terminate your participation at any time and withdraw without any reason.
    a) I consent, begin the study
    b) I do not consent, I do not wish to participate

Questionnaire

3. What is your name?

4. What is your gender?
    a. Male
    b. Female
    c. Prefer not to say

5. What is your email address?

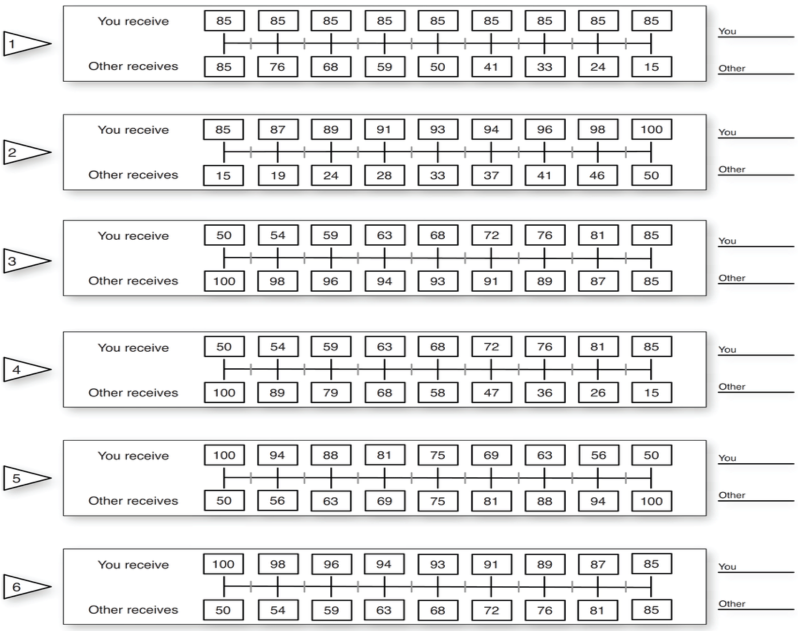
(It is needed to reach you back for the second phase)

6. What is your age?
    a. 18 – 24 years
    b. 24 – 45 years
    c. 45 years
7. What is your highest level of education? (include ongoing education)
    a. None
    b. Primary education
    c. Secondary education
    d. Bachelors or equivalent
    e. Masters or equivalent
    f. Doctoral or equivalent

8. Social preferences

In this task, imagine that you have been randomly paired with another person, whom we will refer to as the other. This other person is someone you do not know and will remain mutually anonymous. All of your choices would be completely confidential.

You will be making a series of decisions about allocating resources between you and this other person. For each of the following questions, please indicate the distribution you prefer most by selecting the button below the payoff allocations. You can only make one selection for each question. Your decisions will yield money for both yourself and the other person. In the example below, a person has chosen to distribute the payoff so that he/she receives 81 dollars, while the anonymous other person receives 69 dollars.



There are no right or wrong answers, this is all about personal preferences. After you have made your decision, select the resulting distribution of money by clicking on button below your choice. As you can see, your choices will influence both the amount of money you receive as well as the amount of money other receives.

9. What is your employment status?
    a. Employed full-time
    b. Full-time student

c. Unemployed / Job seeker
d. Retired
e. Other: _______

10. How many kilometres do you generally drive in a month?
    a. < 100
    b. 101 – 1000
    c. 1001 – 3000
    d. 3001 – 5000
    e. 5001 – 7000
    f. 7001 – 9000
    g. 9001 – 11000
    h. 11001 – 13000
    i. 13001
11. How many years of experience do you have with driving a car?

12. Level of trust you have on the driverless vehicles that interact with other human driven vehicles

S. No.	Item	Strongly disagree	Rather disagree	Neither disagree nor agree	Rather agree	Strongly agree
1	Driverless vehicle can be trusted to carry out journeys effectively.					
2	I trust driverless vehicle to keep my best interests in mind.					
3	My trust in a driverless vehicle will be based on the car manufacturer's reputation for safety and reliability.					
4	My trust in driverless vehicle will be based on the reliability of the underlying technologies.					

13. How familiar are you with the concept of automated vehicles?
    (Rating from 1 to 5, where 1 is *never heard of* and 5 is *closely following the development of AVs*)

14. Do you have any driver assistant feature such as cruise control in your car? Which ones? (You may choose more than one option)
    a. Cruise Control: A device in a vehicle which can be switched on to maintain a selected constant speed without the use of the accelerator pedal.
    b. Adaptive Cruise Control: A driver assistance technology that sets a maximum speed for vehicles and automatically slows the speed of the car when traffic is sensed in front of the vehicle.
    c. Lane Keeping Assist: It uses a video camera to detect the lane markings ahead of the vehicle and to monitor the vehicle's position in its lane. When the vehicle begins

to move out of its lane, the system gently, but noticeably counter-steers in order to keep the vehicle in the lane.

d. Automated Lane Change: These systems detect other vehicles using onboard sensors such as camera, radar, and ultrasonic. When it is safe, the system steers automatically and performs the lane change.

B.2 Information sheet for participants and consent form

Please read this information sheet carefully before signing the consent form. If you decide to participate, your signature will be required. If you desire a copy of this information sheet and consent form, you may request one.

Research title

Understanding interactions between automated vehicles and human drivers

Researchers

Shiva Nischal Lingam – MSc student, TU Delft

Email: S.N.LINGAM@student.tudelft.nl

Phone: +31 645432197

Dr. ir. Haneen Farah

Email: h.farah@tudelft.nl

Ir. Anastasia Tsapi

Email: anastasia.tsapi@rhdhv.com

Purpose of study

The purpose of this research study is to understand the interactions between human drivers and automated vehicles. The interactions are studied to improve traffic safety and efficiency.

Experimental procedure and instructions

In this research study, you will be asked to drive in a driving simulator on a designated route that contains routine driving situations along with other traffic.

You will be asked to fill in an online questionnaire during and after the experiment. This experiment will take about 70 minutes of your time. This time also includes briefing to explain the experiment and breaks between different scenarios. Further instructions will be provided during the experiment.

Before the experiment

On the day of the experiment, you will be briefed shortly about the experiment where other instructions will be made clear to you.

During the experiment

First, you will be allowed to drive freely in the driving simulator to get familiarize and comfortable with the equipment and environment. At the start of every scenario, you will receive an indication from the researcher to start driving (in the simulator). You are expected to perform right-turns at every intersection that you see on the route. While driving, you are free to make your driving decisions. Your only objective during the driving would be to reach the destination as quickly as possible by following all traffic rules.

Once you reach the destination, which is one scenario, you will be asked four questions about your experience while driving. Similar task will be provided to you in all the 12 driving scenarios, excluding the familiarisation drive.

After the experiment

After 12 scenarios of driving and a small break, you will be asked to fill a 2-minute-long online questionnaire related to your driving experiences. On successful competition of the experiment, you will receive a €10 bol.com voucher as a kind gesture.

Risks and safety

We believe that there are no major risks associated with this research study. However, some of the participants might experience minor nausea while driving in the simulator. To minimise nausea, the driving scenarios are designed for shorter duration. If you experience discomfort, you can withdraw from the experiment at any instance.

Strict approved measures are followed to minimise the risk of spreading coronavirus and ensure safety of participants and researcher. Social distancing of 1.5 meters will be maintained throughout the experiment. You are asked to wear gloves before driving the simulator. All the study equipment will be sanitized after every participant use. **In accordance with RVIM-guidelines for COVID-19, we request you not to travel via public transport for the experiment.** If you have symptoms, we request you not to attend the experiment for the safety of you and others.

Data storage and confidentiality

We will safely store data in a secured research repository called Project Storage at TU Delft. The data is regarded as confidential and it will not be shared with external users beyond study group researchers. A month after the end of experiment, the data from both phases is anonymized and aggregated. During this process, personal data such as name, age group, profession, driving experience, gender, social preferences and email addresses will be deleted from the database. If you need information on your data, please contact the researcher within a month after the experiment. After this period, we cannot trace back and provide you the data as the processed data will not have your personal information. Observations will be generated from the processed data and the observations might be published in the academic proceedings. The processed data will be shared on 4TU.Research for future research purposes.

Participant rights

Your participation in this experiment is voluntary. So, you have the right to refuse to follow instructions of the experiment. You also have a right to ask questions about this research at any stage of the experiment. In addition, you have the right to withdraw at any stage of this research. If so, your data will not be used for analysis and it will be deleted from all the databases.

Please express your consent by filling the questionnaire below.

Consent Form for the study – “Understanding interactions between automated vehicles and human drivers”

Please tick the appropriate boxes	Yes	No
Taking part in the study		
I have read and understood the study information dated [DD/MM/YYYY], or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	□	□

I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	◻	◻
I understand that taking part in the study involves driving in a driving simulator and completing questionnaires before, during and after the experiment that will include questions related to experiences during the experiment.	◻	◻
Risks associated with participating in the study		
I understand that the study in a driving simulator could cause minor nausea and that I can stop the experiment at any time I so desire.	◻	◻
Use of the information in the study		
I understand that information I provide will be used in reports, scientific publications or may be presented in conferences on traffic safety, traffic psychology, or relevant fields	◻	◻
I understand that personal information collected about me that can identify me, such as my name, email address or contact details, gender, age group, profession and education level will not be shared to anyone beyond the study team.	◻	◻
I agree that my answers in the survey questionnaires can be quoted in research outputs anonymously	◻	◻
Future use and reuse of the information by others		
I give permission that all the data collected during the experiment and questionnaires filled by me can be archived anonymously in the repository of TU Delft so it can be used for future research and learning	◻	◻
Distancing	◻	◻
I will maintain at least 1.5 meters distance from the researcher during the experiment		
Travelling	◻	◻
I will avoid taking public transport when travelling to and from the experiment location		
Exclusion	◻	◻
I do not participate if I have cold-like symptoms, or cough, or experience a shortness of breath, loss of smell or taste, or have a fever		
Hygiene		

All objects and surfaces a participant can come into contact during the experiment will be disinfected before and after the experiment.

Signatures

______________________	______________________	________
Name of participant	Signature	Date

I have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

Shiva Nischal Lingam	___________________	______
Researcher name	Signature	Date

In case of any questions / doubts / clarifications regarding the study or your rights as a research participant, contact:

Shiva Nischal Lingam, +31 645432197, S.N.LINGAM@student.tudelft.nl

B.3 Pre-experiment briefing

Hi,

Thank you for being a part of our research. This sheet briefs you about the experiment and the steps that you need to take. So, please read it carefully.

About the experiment

The purpose of this study is to understand the interactions between human driven vehicles and automated vehicles. Throughout this experiment, you will drive in different scenarios where you will interact with automated vehicles consisting of different communication systems.

Time required

This experiment will take a maximum of 70 minutes. There are three runs where you are asked to drive on a route (around 8kms with T-intersections). Each run takes around 10 minutes to drive and hence overall driving time would be 30 minutes. The rest of the time will be utilised in performing familiarizing drive, taking short breaks, and filling out questionnaires.

Risks and safety

We believe that there are no major risks associated with this research study. However, some of the participants might experience minor nausea while driving in the simulator. If you experience discomfort, you can report the researcher and withdraw from the experiment at any instance.

Once you read the above instructions, you are ready to start the experiment.

Experiment steps

First, drive in a demo run where you will familiarize yourself with the vehicle controllers (e.g., steering and pedals), and the driving environment. The familiarization drive takes around 10 minutes.

Second, imagine a situation for this experiment

"You are traveling to the office for an important meeting. You travel 8 kms (roughly) by following the mandatory turn signs at the intersections along the route. During the right turn, you interact with vehicles on other lanes. These vehicles may or may not yield. Reach the office by driving close to the speed limits."

After indication by researcher, you will start to drive. The speed limit of the roads is 80kmph and the advisory speed limit at the intersections is 50kmph. You will approach the first right turn sign at a speed of 50kmph. After passing the turn sign, you are free to make any driving decisions.

Please keep an eye on other traffic and drive responsibly by adhering the traffic rules. At the intersections, the interacting automated vehicles will drive in a driverless mode. These vehicles communicate in a form that differs with each run. In our experiment, driverless vehicles communicate explicitly through a display on top of vehicle (see Figure 43) or a signalling device on road (see Figure 44) at the intersection. **These communication forms represent vehicles' intent but not traffic rules.** The colour purple expresses the vehicles' intent to cross the intersection first and maintains speed around 50kmph. On the other hand, green represents its intent to slow down. You are free to comply or not with the intent of driverless vehicles in our experiment.

Your ultimate aim is to reach the office by driving near speed limit, following the traffic rules, and driving as you would do in real life.

Figure 43: Automated vehicle with the absence of human in the driver seat. A light display on top of vehicle expresses vehicle intent to drive first (purple), or second (green) at intersection.

Figure 44: Signalling device expresses intent of automated vehicle to drive first (purple), and second (green) at intersection.

Finally, once you reach the destination, stop your car. You are asked to fill a questionnaire on your experiences in the last run. Similar process is repeated for three times.

End of experiment

You are provided with a post-experiment questionnaire and a researcher asks few questions about your experiences during the experiment. This step marks the end of experiment.

B.4 Mid-experiment questionnaire

Participant ID: ____

Please circle your choices for every scenario.

1. What is the scenario?
   a) Scenario 1
   b) Scenario 2
   c) Scenario 3

2. How critical was the situation in this scenario?

Harmless			Unpleasant			Dangerous			Uncontrollable

Note: The “interacting vehicle” is the driverless **blue car** that drives from your ***left*** at the intersection.

3. On a scale of 1 to 10, What is your level of trust with the interacting vehicles with (or without) communication system in this scenario?

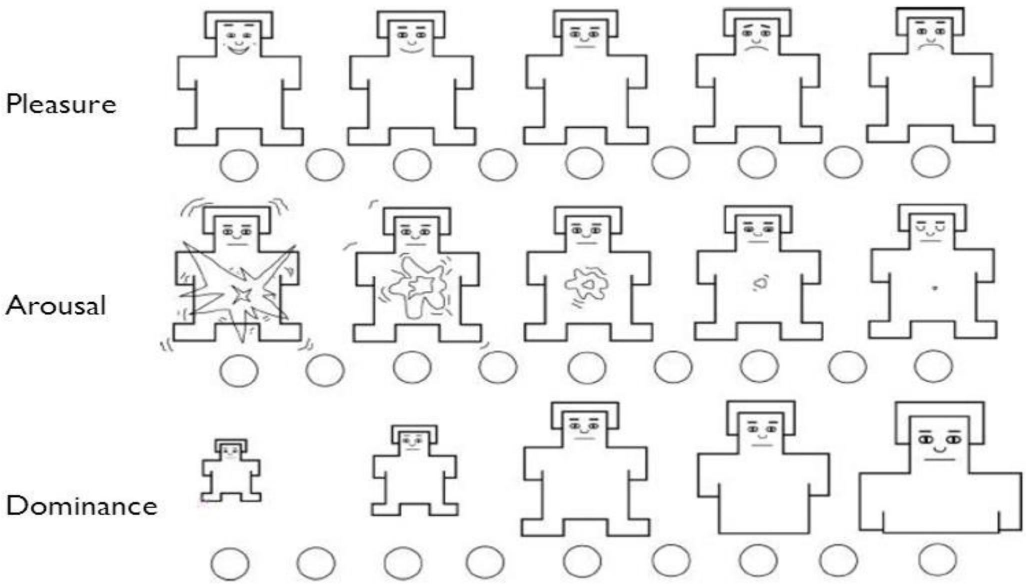
1 = Not at all   10 = Extremely

1	2	3	4	5	6	7	8	9	10

4. My judgements of the interaction system [i.e., communicating display (if any) + vehicle behavior of driverless blue cars] is….

1	useful	_|_|_|_|_	useless
2	pleasant	_|_|_|_|_	unpleasant
3	bad	_|_|_|_|_	good
4	nice	_|_|_|_|_	annoying
5	effective	_|_|_|_|_	superfluous
6	irritating	_|_|_|_|_	likeable
7	assisting	_|_|_|_|_	worthless
8	undesirable	_|_|_|_|_	desirable
9	raising alertness	_|_|_|_|_	sleep-inducing

5. On a pictorial scale, what is your overall feeling with the interacting vehicles in this run?



6. Please select the point on each scale that best indicates your experience in this scenario.

<u>Mental Demand</u>: How much mental and perceptual activity was required (e.g., thinking, deciding, calculating, remembering, looking, searching, etc)? Was the mission easy or demanding, simple or complex, exacting or forgiving?

Low High

<u>Physical Demand</u>: How much physical activity was required (e.g., pushing, pulling, turning, controlling, activating, etc.)? Was the mission easy or demanding, slow or brisk, slack or strenuous, restful or laborious?

Low High

<u>Temporal Demand</u>: How much time pressure did you feel due to the rate or pace at which the mission occurred? Was the pace slow and leisurely or rapid and frantic?

Low High

<u>Performance</u>: How successful do you think you were in accomplishing the goals of the mission? How satisfied were you with your performance in accomplishing these goals?

Low High

<u>Effort</u>: How hard did you have to work (mentally and physically) to accomplish your level of performance?

Low High

<u>Frustration</u>: How discouraged, stressed, irritated, and annoyed versus gratified, relaxed, content, and complacent did you feel during your mission?

Low High

B.5 Post-experiment questionnaire

Dear participant,

Now, you are one step away from completing the experiment. Please answer the following questions that help the researchers to understand your overall experience.

1. What is your current level of trust on the driverless vehicles that interact with normal vehicles (i.e., human driven vehicles)?

Item	Strongly disagree	Rather disagree	Neither disagree nor agree	Rather agree	Strongly agree
Driverless vehicles can be trusted to carry out journeys effectively.					
I trust driverless vehicles to keep my best interests in mind.					
My trust in a driverless vehicles will be based on the car manufacturer's reputation for safety and reliability.					
My trust in driverless vehicles will be based on the reliability of the underlying technologies.					

2. Please answer the following questions on your virtual experience.

Instructions: Circle how much each symptom below is affecting you **right now**.

General discomfort	None	Slight	Moderate	Severe
Fatigue	None	Slight	Moderate	Severe
Headache	None	Slight	Moderate	Severe
Eye strain	None	Slight	Moderate	Severe
Difficulty focusing	None	Slight	Moderate	Severe
Salvation increases	None	Slight	Moderate	Severe
Sweating	None	Slight	Moderate	Severe
Nausea	None	Slight	Moderate	Severe
Difficulty concentrating	None	Slight	Moderate	Severe
Fullness of the head	None	Slight	Moderate	Severe
Blurred vision	None	Slight	Moderate	Severe
Dizziness with eyes open	None	Slight	Moderate	Severe
Dizziness with eyes closed	None	Slight	Moderate	Severe
*Vertigo	None	Slight	Moderate	Severe
**Stomach awareness	None	Slight	Moderate	Severe
Burping	None	Slight	Moderate	Severe

* Vertigo is experienced as loss of orientation with respect to vertical upright

** Stomach awareness is usually used to indicate a feeling of discomfort which is just short of nausea

3. Do you think that your driving behavior was different in interactions with a driverless vehicle with communication system when compared to those vehicles without communication system?

☐ Yes

☐ No

4. Please answer the following questions on virtual presence.

	None at all						A great deal
How much were you able to control events?	○	○	○	○	○	○	○
How responsive was the environment to actions that you initiated (or performed)?	○	○	○	○	○	○	○
How natural did your interactions with the environment seem?	○	○	○	○	○	○	○
How much did the visual aspects of the environment involve you?	○	○	○	○	○	○	○
How natural was the mechanism which controlled movement through the environment?	○	○	○	○	○	○	○
How compelling was your sense of objects moving through space?	○	○	○	○	○	○	○
How much did your experiences in the virtual environment seem consistent with your real-world experiences?	○	○	○	○	○	○	○
How compelling was your sense of moving around inside the virtual environment?	○	○	○	○	○	○	○
How involved were you in the virtual environment experience?	○	○	○	○	○	○	○
How closely were you able to examine objects?	○	○	○	○	○	○	○

How well could you examine objects from multiple viewpoints?	○	○	○	○	○	○	○
Were you able to anticipate what would happen next in response to the actions that you performed?	○	○	○	○	○	○	○
How completely were you able to actively survey or search the environment using vision?	○	○	○	○	○	○	○
How much delay did you experience between your actions and expected outcomes?	○	○	○	○	○	○	○
How quickly did you adjust to the virtual environment experience?	○	○	○	○	○	○	○
How proficient in moving and interacting with the virtual environment did you feel at the end of the experience?	○	○	○	○	○	○	○
How well could you concentrate on the assigned tasks or required activities rather than on the mechanisms used to perform those tasks or activities?	○	○	○	○	○	○	○
How much did the visual display quality interfere or distract you from performing assigned tasks or required activities?	○	○	○	○	○	○	○
How much did the control devices interfere with the performance of assigned tasks or with other activities?	○	○	○	○	○	○	○

Interview questions

1. Did you find the communication systems of driverless vehicles helpful in your decision making? If yes, how?
2. How do you rank the communication systems based on your preference? Why?
3. Why did (did not) change your driving behavior when interacting with different communication systems?
4. What additional information do you need during the interaction that helps you to understand the intention of driverless vehicle easily and feel safer?
5. Do you think that there was a difference in the driving style of driverless vehicles – aggressive vs defensive? If so, which scenarios helped you to distinguish it?
6. What is your overall experience of the experiment?

B.6 Post-experiment debriefing

"Your participation in the research builds our future."

Hurrah! You have successfully completed the experiment. Before the start of experiment, you were provided with information on the research and the experiment. However, some parts of information is concealed to minimize any changes in your driving behavior and perception.

First, the actual aim of this research is to investigate the *effects of automated vehicles' explicit communication signals (i.e., external human-machine interfaces) on human drivers' interactions*. We are focusing on your perception and response (i.e., crossing behavior) to these signals at intersections.

Second, display on top of vehicle and traffic signal at intersections is one of the many forms to communicate the intention of driverless vehicle. You could argue that your perception of signals and driving behavior might differ with the design of the communication forms. However, our research does not focus on the design of these communication signals. Instead, this study focuses on whether the driverless vehicle should have an explicit communication signal. If so, where should it be placed (i.e., on vehicle vs on road infrastructure) such that the signal improves driver acceptance and response in the interactions. The reason for not providing this information is as follows:

Variation in opinion: We are humans and we have curiosity. Sometimes, curiosity leads to searching for answers even before the questions are asked. This could lead to biased opinions. For instance, consider that a curious participant is informed in advance that this experiment focuses on communicative interactions with automated vehicles. He/she might have done some research before experiment to know the available forms of communication signals for a driverless car. If this communication signal is different to that in the experiment, he/she might form a different opinion. Change in opinion might alter their perception; which might lead to a different driving behavior while interacting with automated vehicle. This defeats the purpose of research as it leads to unrealistic observations.

Your participation is invaluable and we are thankful from the bottom of our hearts. Your contribution will help the scientific community in understanding the human driver perception and behavior in an effective way. This research offers a direction to improve the social interactions with automated vehicles; thereby, leading to traffic safety and efficiency.

In case you have any questions or curious about the results, please contact

Shiva Nischal Lingam – MSc student, TU Delft

Email: S.N.LINGAM@student.tudelft.nl

Appendix C: Learning effects

Table 17: Correlation of driver behavior variables with yielding AVs over number of interactions.

	AV interaction number		
Behavior variables	Correlation Coefficient	Sig. (2-tailed)	N
Approaching speed (m/s)	-0.030	0.465	607
Maximum acceleration (m/s2)	0.038	0.350	607
Maximum deceleration (m/s2)	0.005	0.896	607
Minimum speed (m/s)	-0.058	0.154	607
Time to maximum braking (s)	0.038	0.349	607
Crossing decision (0 or 1)	-0.011	0.795	607
Crossing time (s)	0.034	0.401	607
Critical events (0 or 1)	0.051	0.208	607

Table 18: Correlation of driver behavior variables with yielding AVs over number of interactions (as per scenario).

	AV interaction number								
	Baseline			eHMI on vehicle			eHMI on infrastructure		
Behavior variables	r_s	Sig. (2-tailed)	N	r_s	Sig. (2-tailed)	N	r_s	Sig. (2-tailed)	N
Approaching speed (m/s)	0.000	0.998	203	-0.086	0.227	200	0.005	0.940	204
Maximum acceleration (m/s2)	-0.003	0.967	203	0.030	0.676	200	0.083	0.239	204
Maximum deceleration (m/s2)	0.001	0.987	203	-0.008	0.909	200	0.027	0.700	204
Minimum speed (m/s)	-0.069	0.326	203	-0.072	0.313	200	-0.032	0.650	204
Time to maximum braking (s)	0.061	0.384	203	-0.038	0.592	200	0.102	0.149	204
Crossing decision (0 or 1)	0.030	0.673	203	-0.006	0.928	200	-0.064	0.365	204
Crossing time (s)	0.019	0.784	203	0.076	0.288	200	0.004	0.952	204
Critical events (0 or 1)	0.116	0.100	203	-0.005	0.947	200	0.051	0.471	204

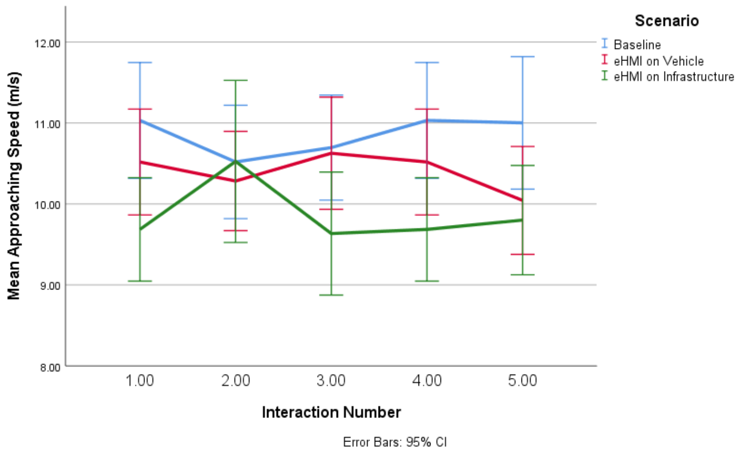


Figure 45: Mean approaching speed with yielding AVs over multiple interactions (as per scenario).

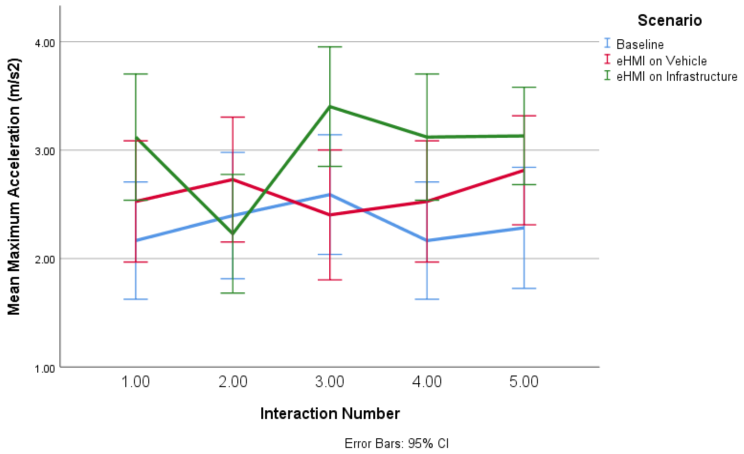


Figure 46: Mean maximum acceleration with yielding AVs over multiple interactions (as per scenario).

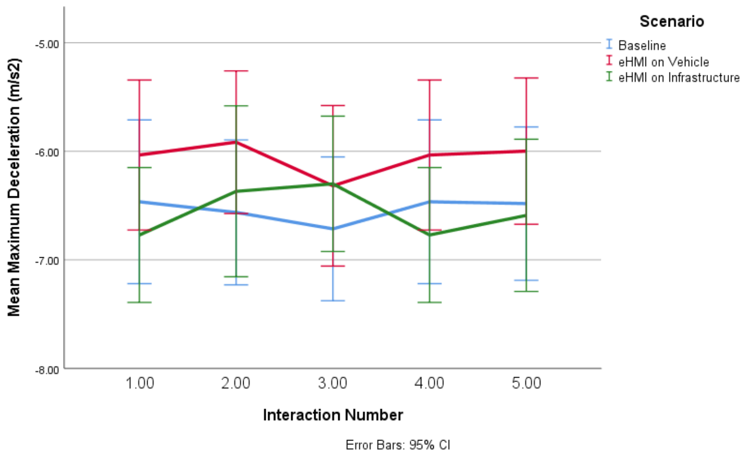


Figure 47: Mean maximum deceleration with yielding AVs over multiple interactions (as per scenario).

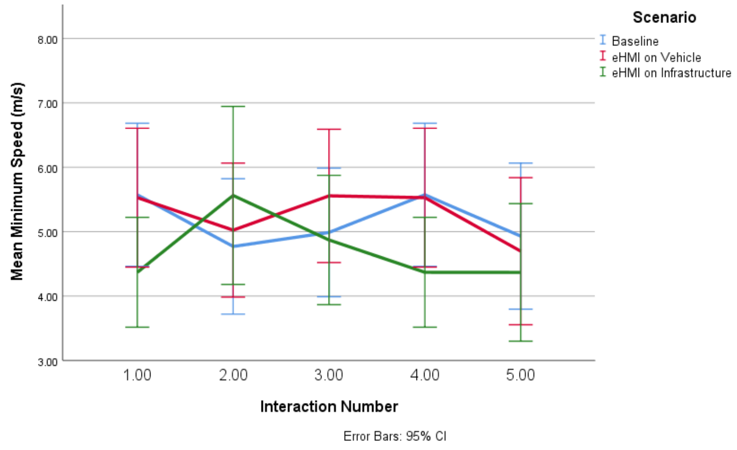


Figure 48: Mean minimum speed with yielding AVs over multiple interactions (as per scenario).

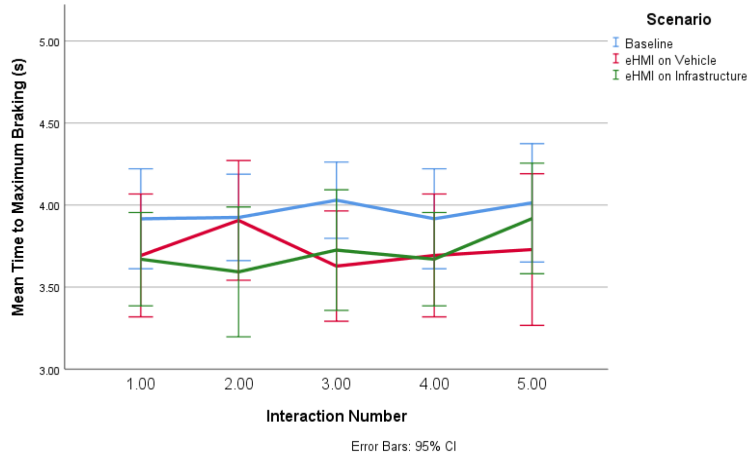


Figure 49: Mean time to maximum braking with yielding AVs over multiple interactions (as per scenario).

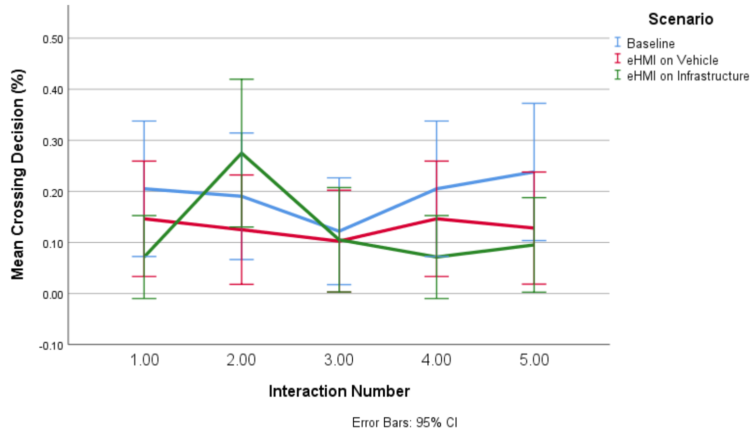


Figure 50: Mean crossing decision with yielding AVs over multiple interactions (as per scenario).

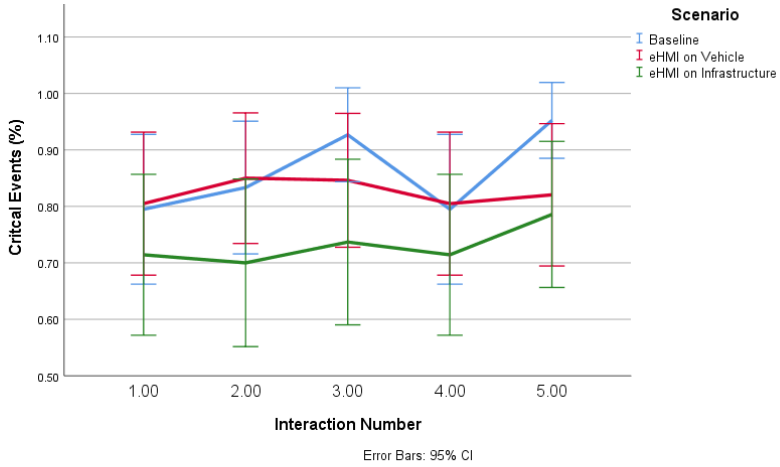


Figure 51: Mean critical events with yielding AVs over multiple interactions (as per scenario).

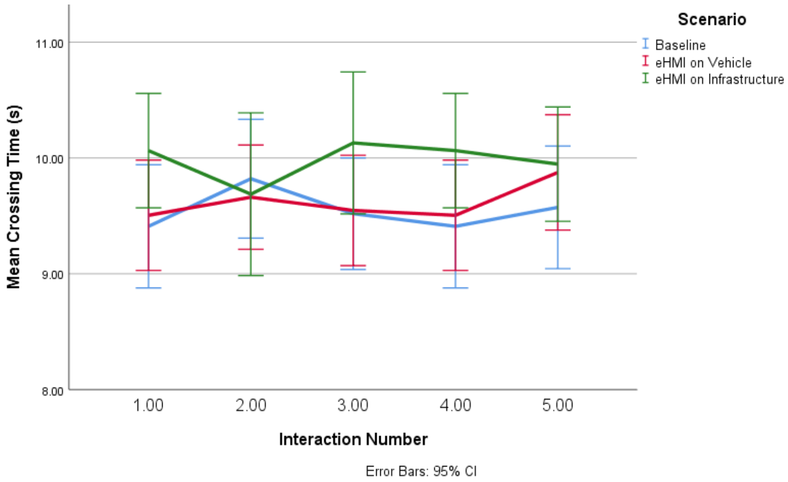


Figure 52: Mean crossing time with yielding AVs over multiple interactions (as per scenario).

Table 19: Correlation of driver behavior variables with non-yielding AVs over number of interactions.

	AV interaction number		
Driver behavior variables	Correlation Coefficient	Sig. (2-tailed)	N
Approaching speed (m/s)	0.031	0.459	569
Maximum acceleration (m/s2)	0.003	0.950	569
Maximum deceleration (m/s2)	0.047	0.258	569
Minimum speed (m/s)	0.048	0.255	569
Time to maximum braking (s)	-0.053	0.204	569
Crossing decision (0 or 1)	0.002	0.971	569
Crossing time (s)	-0.107	0.111	569
Critical events (0 or 1)	0.030	0.480	569

Table 20: Correlation of driver behavior variables with non-yielding AVs over number of interactions (as per scenario).

	AV interaction number								
	Baseline			eHMI on vehicle			eHMI on infrastructure		
Driver behavior variables	r_s	Sig. (2-tailed)	N	r_s	Sig. (2-tailed)	N	r_s	Sig. (2-tailed)	N
Approaching speed (m/s)	0.083	0.255	192	0.049	0.502	187	-0.039	0.591	190
Maximum acceleration (m/s2)	-0.006	0.939	192	0.061	0.406	187	-0.042	0.567	190
Maximum deceleration (m/s2)	0.058	0.426	192	-0.013	0.855	187	0.100	0.170	190
Minimum speed (m/s)	0.052	0.477	192	0.047	0.527	187	0.047	0.516	190
Time to maximum braking (s)	-0.051	0.478	192	-0.022	0.770	187	-0.084	0.250	190
Crossing decision (0 or 1)	-0.015	0.839	192	-0.055	0.458	187	0.083	0.254	190
Crossing time (s)	-0.112	0.122	192	-0.120	0.102	187	-0.091	0.212	190
Critical events (0 or 1)	0.016	0.829	192	0.046	0.532	187	0.048	0.514	190

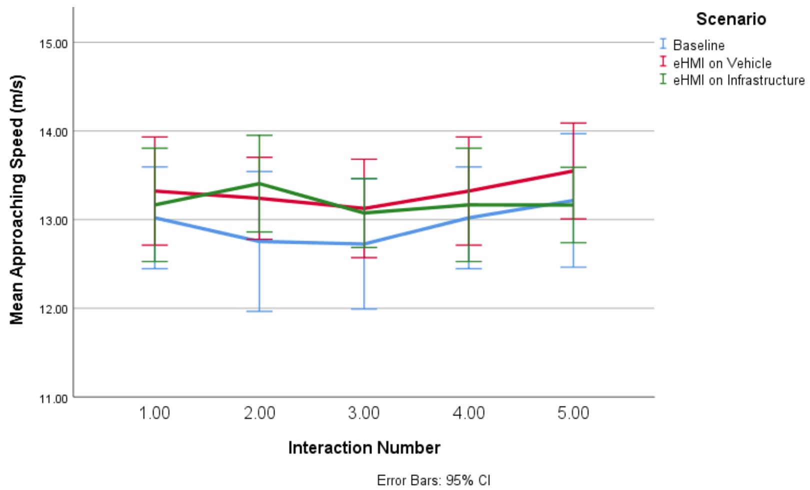


Figure 53: Mean approaching speed with non-yielding AVs over multiple interactions (as per scenario).

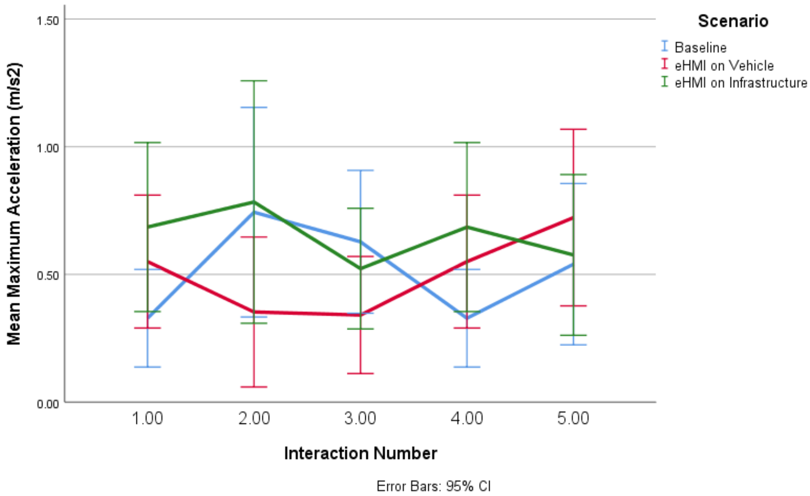


Figure 54: Mean maximum acceleration with non-yielding AVs over multiple interactions (as per scenario).

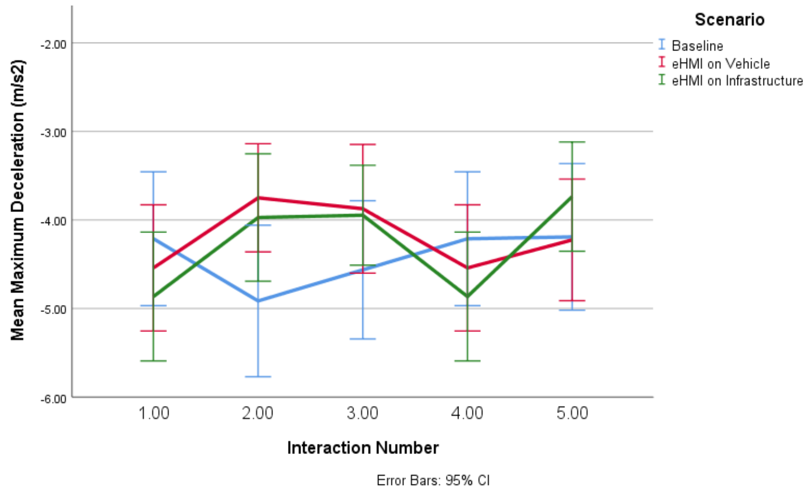


Figure 55: Mean maximum deceleration with non-yielding AVs over multiple interactions (as per scenario).

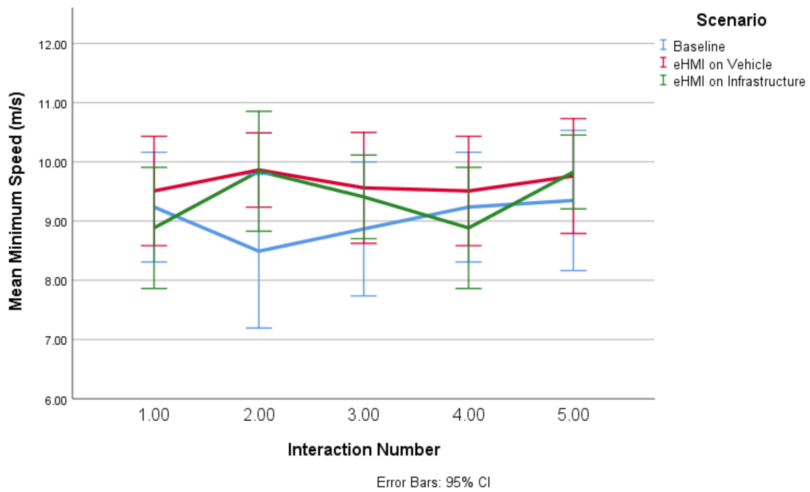


Figure 56: Mean minimum speed with non-yielding AVs over multiple interactions (as per scenario).

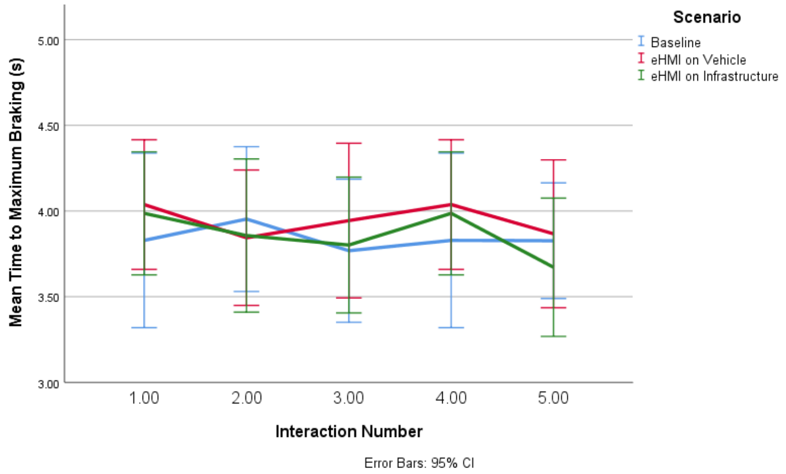


Figure 57: Mean time to maximum braking with non-yielding AVs over multiple interactions (as per scenario).

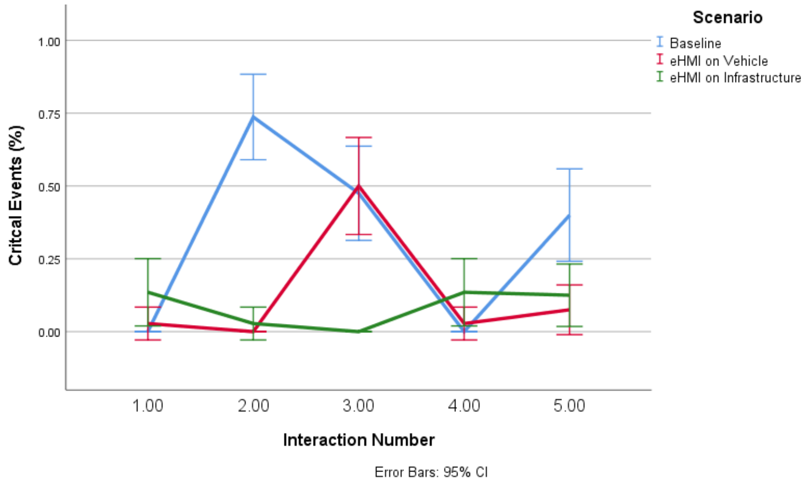


Figure 58: Mean critical events with non-yielding AVs over multiple interactions (as per scenario).

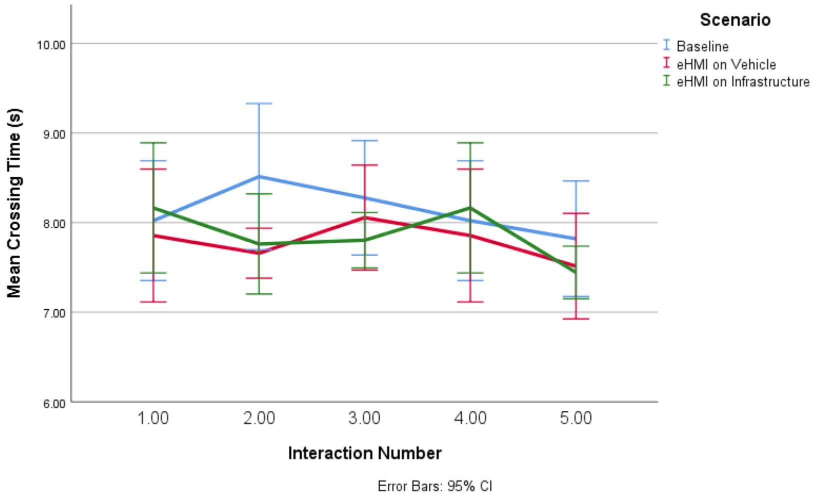


Figure 59: Mean crossing time with non-yielding AVs over multiple interactions (as per scenario).

Appendix D: Modeling

Table 21: Multicollinearity test results for preference model.

Variables	Standardized Coefficients	t	Sig.	Collinearity Statistics	
	Beta			Tolerance	VIF
(Constant)		-0.201	0.841		
Gender	0.012	0.125	0.901	0.871	1.148
Age	0.106	0.668	0.505	0.316	3.164
Education	-0.015	-0.143	0.887	0.719	1.390
Exposure (kms)	0.020	0.191	0.849	0.749	1.336
Employment	0.030	0.259	0.796	0.575	1.738
Social preferences	0.002	0.016	0.987	0.836	1.196
Driver knowledge on AVs	0.017	0.172	0.863	0.862	1.160
Initial trust on AVs	-0.025	-0.259	0.796	0.877	1.140
Scenario	0.326	3.652	0.000	0.996	1.004
Experience (yrs)	-0.145	-0.832	0.407	0.263	3.800
Perceived criticality	0.089	0.812	0.418	0.532	1.880
Trust	0.225	1.823	0.071	0.423	2.366
Usefulness	0.247	1.525	0.130	0.246	4.062
Satisfaction	0.044	0.234	0.816	0.183	5.460
Pleasure	-0.026	-0.184	0.854	0.327	3.061
Arousal	-0.104	-1.003	0.318	0.597	1.674
Dominance	-0.009	-0.105	0.916	0.856	1.169
Mental demand	-0.220	-1.563	0.121	0.326	3.070
Physical demand	0.025	0.180	0.858	0.334	2.991
Temporal demand	0.062	0.544	0.588	0.501	1.996
Performance	-0.187	-1.979	0.050	0.723	1.383
Frustration	0.144	1.063	0.290	0.350	2.859
Effort	-0.107	-0.992	0.323	0.558	1.792

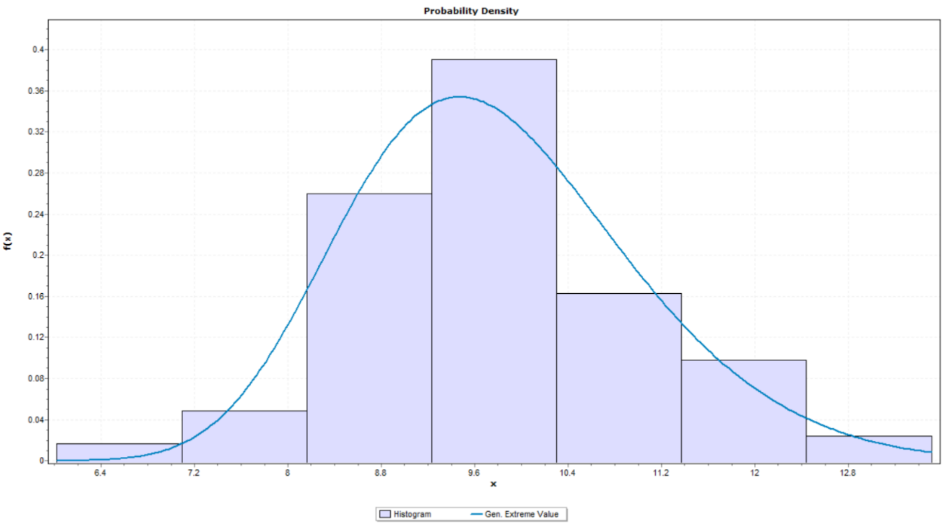


Figure 60: Beta distribution of critical events data.

Table 22: Different distribution test results for the critical events. The distribution with the least AIC and BIC values is a better fit.

Distributions	Loglikelihood	AIC	BIC
Poisson	-5336.48	10674.95	10678.45
Binomial	-1176.21	2356.424	2363.418
Exponential	-62.0195	126.038	129.536
Gamma	-44.0826	92.165	99.159
Beta	99.19033	-194.381	-187.386

Table 23: Multicollinearity test results for critical events model.

Variables	Standardized Coefficients	t	Sig.	Collinearity Statistics	
	Beta			Tolerance	VIF
(Constant)		3.500	0.001		
Gender	-0.040	-0.702	0.484	0.620	1.612
Age	-0.026	-0.288	0.774	0.249	4.024
Ed	-0.011	-0.176	0.861	0.538	1.859
Exp(kms)	-0.102	-1.402	0.164	0.375	2.664
Exp(yrs)	0.051	0.505	0.615	0.196	5.111
Emp	-0.088	-1.268	0.208	0.415	2.412
SV	-0.018	-0.275	0.784	0.463	2.162
K	0.040	0.674	0.502	0.569	1.757
IT	-0.080	-1.453	0.150	0.656	1.525
Run	0.321	5.633	0.000	0.616	1.624
PC	0.020	0.289	0.773	0.417	2.397
Trust	-0.048	-0.612	0.542	0.329	3.041
Usefulness	0.002	0.025	0.980	0.207	4.831
Satisfaction	0.049	0.415	0.679	0.143	7.001
Pleasure	-0.009	-0.098	0.922	0.246	4.061
Arousal	-0.115	-1.815	0.073	0.493	2.027
Dominance	0.025	0.382	0.703	0.470	2.129
Mental demand	-0.069	-0.808	0.421	0.271	3.691
Physical demand	0.197	2.277	0.025	0.268	3.732
Temporal demand	-0.138	-1.984	0.050	0.413	2.422
Performance	-0.076	-1.151	0.253	0.460	2.175
Frustration	-0.002	-0.023	0.982	0.312	3.205
Effort	0.030	0.440	0.661	0.418	2.391
Approaching speed	0.026	0.135	0.893	0.052	19.098
Maximum acceleration	0.102	1.172	0.244	0.263	3.799
Maximum deceleration	-0.006	-0.068	0.946	0.235	4.254
Minimum speed	-0.259	-1.528	0.130	0.069	14.394
Time to maximum braking	0.104	1.735	0.086	0.558	1.791
Crossing decision	-0.249	-1.776	0.079	0.102	9.838

Table 24: Gamma distribution test results for the crossing time data.

	Kolmogorov-Smirnov test	Anderson-Darling test
Critical value	0.123	2.501
Statistic	0.09	0.882
Reject null hypothesis	No	No

Table 25: Multicollinearity test results for crossing time model.

Variables	Standardized Coefficients	t	Sig.	Collinearity Statistics	
	Beta			Tolerance	VIF
(Constant)		19.775	0.000		
Gender	0.023	1.051	0.296	0.624	1.602
Age	0.027	0.801	0.425	0.250	3.999
Education	-0.031	-1.337	0.185	0.548	1.823
Exposure(kms)	-0.046	-1.670	0.098	0.379	2.640
Experience(yrs)	0.033	0.855	0.395	0.197	5.084
Employment	-0.033	-1.250	0.214	0.414	2.414
Social preferences	-0.050	-2.038	0.044	0.483	2.069
Driver knowledge on AVs	0.018	0.790	0.431	0.570	1.754
Initial trust	0.006	0.271	0.787	0.641	1.559
Scenario	0.055	2.228	0.028	0.481	2.077
Perceived criticality	-0.036	-1.361	0.177	0.425	2.352
Trust	-0.039	-1.329	0.187	0.334	2.996
Usefulness	-0.010	-0.278	0.782	0.207	4.827
Satisfaction	0.067	1.513	0.134	0.146	6.842
Pleasure	-0.087	-2.632	0.010	0.265	3.774
Arousal	-0.049	-2.029	0.045	0.498	2.010
Dominance	0.028	1.150	0.253	0.476	2.102
Mental demand	-0.015	-0.457	0.649	0.270	3.709
Physical demand	0.039	1.173	0.244	0.257	3.886
Temporal demand	-0.057	-2.142	0.035	0.416	2.405
Performance	-0.028	-1.118	0.267	0.459	2.177
Frustration	0.012	0.392	0.696	0.313	3.199
Effort	0.021	0.796	0.428	0.420	2.380
Approaching speed	-0.278	-4.059	0.000	0.062	16.174
Maximum acceleration	-0.121	-3.923	0.000	0.303	3.298
Maximum deceleration	-0.017	-0.482	0.631	0.236	4.243
Minimum speed	-0.077	-1.191	0.237	0.069	14.537
Time to maximum braking	0.024	1.038	0.302	0.547	1.828
Crossing decision	-0.305	-6.938	0.000	0.150	6.657
Critical events	-0.103	-2.690	0.009	0.196	5.098

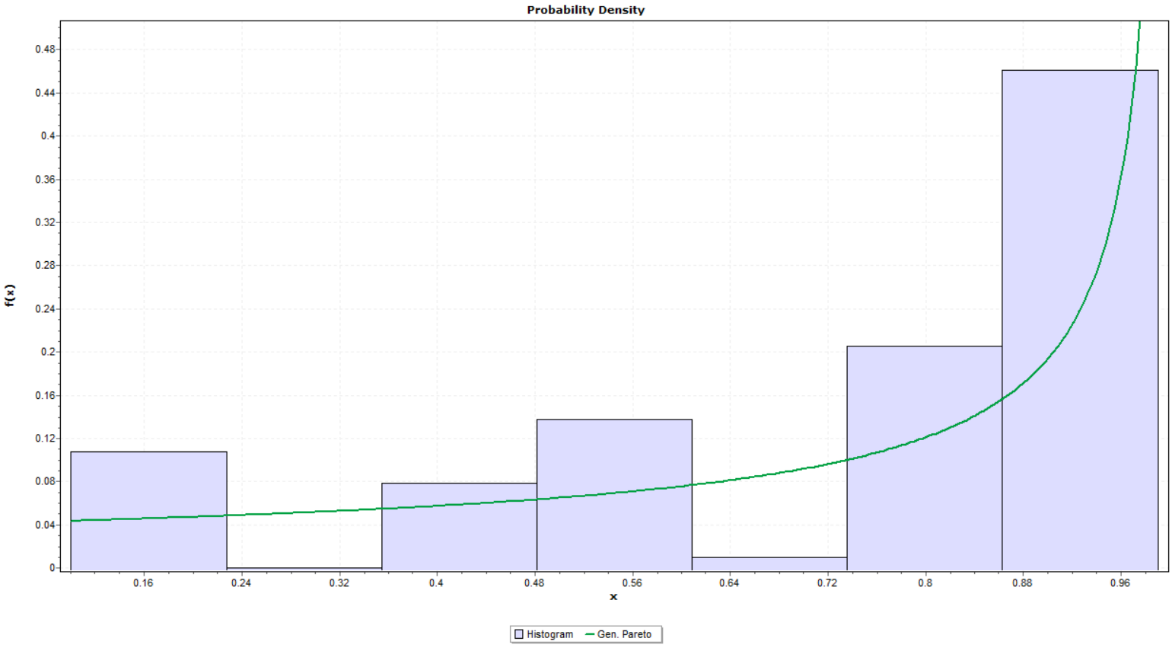


Figure 61: Gamma distribution of crossing time data.