TIL Master Thesis

The effect of eHMI design on cyclists' crossing behaviour when interacting with automated vehicles in a shared space

A Virtual Reality study on cyclist-AV interaction

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Mobility in eXtended Reality

Summary

As Automated Vehicles (AVs) become increasingly integrated into urban mobility and transportation, understanding how vulnerable road users (VRUs) interact with them is crucial for ensuring safety and efficiency. AVs promise benefits such as reduced congestion and emissions, but they lack the human driver's ability to engage in natural non-verbal communication, such as eye contact and hand gestures, which is critical for safe interaction in traffic. To bridge this communication gap, external Human-Machine Interfaces (eHMIs) have been developed. These interfaces use visual, auditory, or haptic cues (e.g., text, symbols, lights) to signal the AV's intentions to nearby road users. One particularly complex environment for AV integration is a shared space, which is an urban area specifically designed without traditional traffic signs, signals or right-of-way rules, where interactions rely heavily on social cues. The lack of human drivers in AVs makes communication even more challenging. Therefore, the use of eHMIs forms a potential solution for ensuring safe and efficient VRU-AV interactions. Virtual Reality (VR) is a valuable research method for studying these interactions under safe and controlled conditions. VR experiments allow for the creation of immersive and realistic traffic scenarios to evaluate how different eHMI designs influence VRU's behaviour.

Although substantial research has focused on pedestrian-AV interactions, studies examining cyclist-AV interactions remains very limited. Given the differences in movement, speed, and positioning between cyclists and pedestrians, findings from pedestrian studies cannot be directly applied. Therefore, a valuable research gap remains in analyzing cyclist-AV interactions, using eHMIs as communication tools. This study addresses that gap by evaluating the influence of four eHMI designs (no eHMI, textual, symbolic and lights) on cyclists' crossing behaviour in a shared space, using a VR experiment as research method. The main research question that is answered in this study is as follows: *"What is the effect of different eHMIs on cyclists' crossing behaviour when interacting with AVs?"*

The experiment involved a number of participants taking on the role of a cyclist using a VR bicycle simulator. Throughout a series of crossing scenarios they interacted with an AV equipped with one of four eHMI designs to observe their responses. The virtual environment was created in Unreal Engine 5 and represents a fictional shared space area. Each participant encountered 11 scenarios, of which 8 primary scenarios focused on data collection and 3 additional "confusing" scenarios to reduce participant bias. In the primary scenarios, the direction from which the AV approaches stays constant (always from the right-hand side). For each of the four eHMI designs, there is one scenario in which the AV yields to the cyclist and one scenario in which the AV does not yield. In the "confusing" scenarios, the AV's approaching direction varies. They are included solely to prevent participants from anticipating the AV's behaviour, and are not included in the final data analysis.

Objective behavioural data was gathered during the VR experiment, which allows for the calculation of several key measures to assess cyclists' crossing behaviour: crossing initiation time, crossing time, speed change, gazing time, and crossing intention. In addition to the behavioural data, participants completed a post-experiment questionnaire to collect subjective data on demographics, perceived realism of the VR, simulator sickness, level of presence, and subjective perceptions and experiences. In the latter, the participants are asked to evaluate six subjective measures for each eHMI design: perceived risk, perceived safety, trust in AV, clarity of eHMI, decision-making and preferences regarding eHMI design. Together, the objective and subjective metrics provide a comprehensive understanding of how cyclists perceive, interpret and respond to different eHMIs.

The results of the experimental data demonstrated that the use of any eHMI does influence cyclists' crossing behaviour, however the effects were not consistent across all objective measures. Text- and light-based eHMIs facilitated quicker decision-making compared to using no eHMI when the AV is yielding, while the light eHMI also increased the crossing time and gazing time when the AV is not yielding, suggesting a potential uncertainty of the cyclist. The other objective measures did not show any statistically significant differences from the baseline. In contrast, the subjective responses to the questionnaire showed that the presence of any eHMI leads to significantly higher clarity ratings, perceived safety and trust in the AV. Therefore, a gap between perceived clarity and actual behaviour was observed. Determining which eHMI was the most effective and best perceived proved to be difficult and inconclusive. While the symbolic eHMI received the highest ratings across all subjective measures, the differences among the three eHMIs were not significant.

To conclude, this study contributes to the existing literature on cyclist-AV interactions by providing insights into how cyclists' crossing behaviour is affected by different types of eHMIs. While it supports the potential of eHMIs in improving communication between cyclists and AVs, some limitations are worth mentioning. Both traffic scenarios and eHMI designs have been simplified to target the effect of key variables in the experiment. These limitation indicate that further research is needed that evaluates the use of eHMIs in more dynamic mixed-traffic environments, as the complexity brings different challenges to the effective implementation of eHMIs. Furthermore, future work should examine the use of alternative types of eHMIs, such as auditory, haptic and multi-modal eHMIs, to gain a more comprehensive understanding of their potential and effect on cyclists' behaviour. Overall, the findings of this study offers a rich basis for future eHMI development and improvement for real-world implementation.

Contents

1 Introduction

This chapter introduces the topic of the study by outlining the broader context and providing relevant background information. Furthermore, it highlights the need for this research by identifying the existing research gap in literature, and presents the research questions that guide this study. Lastly, it provides an overview of the structure and outline of the study, briefly explaining the contents of each subsequent section.

1.1 Background information

In the pursuit of sustainable and efficient transportation, automated vehicles (AVs) offer a promising innovation with the potential of redefining human interaction with urban mobility. Not only could automated vehicles reduce traffic congestion, optimize energy consumption and minimize emissions through sophisticated driving patterns and real-time data analysis (Rahman and Thill, 2023), but they are also able to stimulate a shift towards shared mobility and alternative energy sources (Taiebat et al., 2018). This is why they will form an integral part of urban transportation and are a key step towards a more environmentally friendly and efficient future. This means that road users will increasingly encounter AVs in traffic in the near future. Thus, understanding how road users interact with AVs is critical in ensuring safety and efficiency in urban mobility. In particular, a key focus lies on so-called vulnerable road users (VRUs), which typically include non-motorized road users such as pedestrians and cyclists, as well as motorcyclists and persons with disabilities or reduced mobility and orientation (European Commission, n.d.). These road users are more susceptible to injury and harm during road interactions, as they have less physical protection in the event of a collision and may be less visible to drivers in certain situations. Therefore with the deployment of more AVs, it is crucial to know how these VRUs would react to AVs in certain traffic situations, in order to mitigate risks and improve overall safety.

Unlike traditional vehicles, AVs often lack a human driver capable of engaging in natural forms of communication, such as eye contact and hand gestures, that help to convey intentions and ensure safe interaction with other road users. The absence of implicit communication thus presents a challenge for safely integrating AVs into mixed traffic environments. To address this challenge, researchers have explored different ways of enabling AVs to communicate their intentions to nearby road users, in particular VRUs such as pedestrians and cyclists. One promising solution is the use of external Human-Machine Interfaces (eHMIs). These interfaces, typically located on the exterior of the AV, can serve as a form of communication between the AV and other road users. It can consist of visual, auditory or haptic signals, such as text displays, symbolic messages, lights and projections (Dey et al., 2020), and serve as a replacement for social cues typically provided by the human driver. Therefore, eHMIs are proposed to compensate for this absence of natural communication abilities in AVs (Lagström and Malmsten Lundgren, 2016).

A specific traffic context that could benefit from the use of eHMIs is a shared space. These urban environments are specifically designed without conventional traffic signs, lights or right-of-way rules (Moody and Melia, 2014). All road users, such as pedestrians, cyclists or vehicles, rely heavily on social interactions and communication to navigate safely and efficiently (Wang et al., 2022). The integration of AVs into these environments present a unique challenge, as the lack of human drivers eliminate these forms of communication. The use of eHMIs could, therefore, potentially play a vital role in facilitating safer interactions between VRUs and AVs.

To understand the interaction between AVs and VRUs and the use of eHMIs, it is essential to collect data from controlled experiments. Conducting such experiments in real-world traffic environments, however, could be costly, logistically challenging and potentially unsafe. While other methods such as interviews or questionnaires can also offer valuable insights into participants' perceptions and preferences, they often do not capture the full complexity of decision-making in traffic situations. An alternative is the use of Virtual Reality (VR), which enables the creation of immersive and realistic traffic scenarios within a safe and controlled environment (Deb et al., 2017). VR experiments allow researchers to analyze the behaviour of VRUs when interacting with AVs under varying conditions, without putting the participants in immediate risk or danger. Such experiments are also able to implement the use of eHMIs to systematically evaluate its impact on the decision-making and perceived safety of the VRU.

1.2 Research gap

From the literature review performed in Section 2, it becomes clear that substantial research has been done on pedestrian-AV interactions, particularly using VR experiments as research method. These studies have demonstrated how eHMIs can be used to enhance communication and increase trust in the AV. The presence of any eHMI has shown to increase pedestrian's perceived safety, trust in AV and user experience when interacting with AVs (Faas, Mathis, and Baumann, 2020).

It is evident that existing studies have predominantly focused on pedestrian-AV interaction, however far less attention has been directed towards the interaction between cyclists and AVs. While certain insights from pedestrian-AV studies can also be useful for cyclist-AV research, the findings may not all be directly applicable. Cyclists exhibit distinct behavioural patterns that might differ from those of pedestrians. For example, cyclists move at higher speeds and differ in mobility and positioning on the road, leading to different interaction dynamics (Eriksson et al., 2019; Che et al., 2021). Their decision-making processes and safety perceptions can also vary from those of pedestrians, which influences how they respond to AVs (Zhang et al., 2020).

Therefore, there remains a valuable gap in research addressing cyclist-AV interactions, in particular with the use of eHMIs as communication tools. These eHMIs are especially useful within so called "shared space" areas, in which regular traffic rules and signs do not apply. In such situations, road users solely rely on the social interaction and communication between one another. Since AVs lack the traditional human communication abilities, interactions in these environments between cyclists and AVs could potentially form dangerous situations (Mohammadi, Bianchi Piccinini, and Dozza, 2024). The use of eHMIs could solve this lack of communication in order to make interactions with other road users safer and more efficient. This means it is important to understand how cyclists' crossing behaviour is influenced by different types of eHMIs. Hence, the goal of this research is to understand the crossing behaviour of cyclists when interacting with AVs in a shared space area, by analyzing the impact of different eHMIs on their behaviour.

1.3 Research questions

The objective of this research is to understand cyclists' crossing behaviour when interacting with an AV in a shared space area, using a virtual reality (VR) experiment. Specifically, the study aims to examine the use of eHMIs to enhance communication between cyclists and AVs and to understand the effect of different eHMI designs on the crossing behaviour of cyclists. The purpose of the research is to gain insights into the effectiveness of eHMIs and how they can be used to contribute to a safer and more efficient interaction between cyclists and AVs. The main research question to be answered in this research is then formulated as follows:

What is the effect of different eHMIs on cyclists' crossing behaviour when interacting with AVs?

To be able to answer the main research question, the following sub-questions are posed:

1. What is theoretically the impact of different eHMIs on the crossing behaviour of cyclists?
2. How are objective aspects of cyclists' crossing behaviour empirically affected by different eHMI designs in a shared space in a VR experiment?
3. How are subjective aspects of cyclists' crossing behaviour—such as perceived risk, safety and trust in the AV—affected by different eHMI designs in a shared space in a VR experiment?

1.4 Research structure

In Section 2, to better understand the research gap, a literature review is performed on pedestrian-AV interactions, cyclist-AV interactions and eHMIs used for improving communication in these dynamics. Also, in this section the concept of "shared space" is further explained and why this particular traffic scenario benefits from the use of eHMIs. The literature review concludes with a conceptual model, which aims at defining the dependent and independent variables in this study, as well as indicating the relations that are analyzed. Furthermore, in Section 3, the methods that are used during the research to answer the research questions are explained. A detailed description of the experimental procedure is provided in this section as well. In Section 4, the results of the VR experiment are given, which are discussed and interpreted in Section 5. In the discussion, the limitations of the research are acknowledged as well as providing recommendations for future work. Finally, in Section 6, the study is concluded by summarizing and providing a reflection of the key findings.

2 Literature review

This literature review aims to explore existing knowledge and research on VRU interaction with automated vehicles (AVs) and evaluating the effectiveness and impact of external human-machine interfaces (eHMIs). The goal is to understand the state-of-the-art of cyclist-AV interactions and the use of eHMIs, and to identify key gaps and opportunities for future research. By first analyzing studies that employ VR experiments to investigate pedestrian-AV interactions, an initial understanding of VRU-AV dynamics is established (Section 2.1). This knowledge is then extended by reviewing the interaction between cyclists and AVs, to understand how they react differently or similarly to pedestrians (Section 2.2). Afterwards, the review delves deeper into the use of eHMIs on AVs, which are used in order to support the decision-making of other road users and to enhance the communication with the AV. It investigates the various types of eHMIs and how its design can affect the behavior of the road user within certain scenarios. Finally, different traffic scenarios will be explored in which communication between AVs and cyclists could benefit from the use of eHMIs, such as shared space areas (Section 2.3). In the conclusion and discussion of the literature review, the most important findings are provided, as well as the research gaps.

2.1 Pedestrian-AV interaction

Pedestrians are one example of VRUs interacting with AVs in traffic scenarios. The use of Virtual Reality (VR) experiments and simulations as a research method presents many benefits in examining these VRU-AV interactions. They are valued for their cost-effectiveness, flexibility in developing various traffic scenarios, safe conduct of user studies, and acceptable ecological validity (Tran, Parker, and Tomitsch, 2021). With precise control over variables and scalability of experiments, researchers can conduct systematic investigations, analyze pedestrian behaviors, and iterate on interface designs efficiently (Schneider and Li, 2019). Therefore, VR experiments are an effective tool in recreating realistic traffic scenarios and collecting data in highly controlled environments (Feng et al., 2021), which is why they are used in a multitude of studies to understand pedestrians' behaviour.

Many studies have conducted research on the crossing behaviour of pedestrians when interacting with AVs using VR experiments. Velasco et al. (2019), for instance, conducted a study in which fifty-five individuals participated, of whom the crossing intentions as well as their trust in automation and perceived behavioral control was reported. They were each presented with several videos showcasing different crossing scenarios, which were shown using VR glasses. The participants were asked several questions on their behavior and trust in automation in the form of a survey. The results indicate that the pedestrian is more likely to cross when a zebra crossing is present, as well as when the gap between them and the AV increases. Furthermore, participants who recognized the vehicle as an AV had lower crossing intentions when compared to interacting with a conventional vehicle. This could be coming from a distrust of the vehicles, as they might be knowledgeable of the limitations of current AVs (Velasco et al., 2019). However, the fact that AVs are still evolving and will be even more reliable in the future, means the trust in AVs will grow as well, possibly making the measured trust values irrelevant. Another way of increasing trust in AVs, is by increasing overall knowledge and familiarity with AVs, as well as increasing knowledge on the potential of AVs (Horowitz et al., 2023).

One way of improving this trust is through the use of eHMIs, which facilitate communication between pedestrians and AVs. These interfaces aim to replicate or replace the traditional forms of communication, such as eye contact or hand signals. A study by Feng, Farah, and Arem (2023) investigated the effect of eHMIs on the crossing intentions of pedestrians in a VR experiment, in which they encountered an AV with three possible eHMIs: no eHMI, an image of a pedestrian, or a projected zebra crossing. Interestingly, participants' crossing intention did not differ between the eHMI and non-eHMI conditions. However, the findings indicated that the presence of an eHMI did have an impact on pedestrians' gazing behavior (Feng, Farah, and Arem, 2023). This means that the use of an eHMI directs the attention of a pedestrian more effectively towards an AV than without the use of an eHMI.

Another study investigated the informational needs of pedestrians towards AVs, in which participants encountered an AV with different types of eHMIs, displaying its intent or its perception of the pedestrian. The findings of the test indicated that any form of eHMI leads to better trust in AVs, perceived safety and user experience when interacting with AVs (Faas, Mathis, and Baumann, 2020). In terms of informational needs of the pedestrian, it showed that status information is the biggest contributor to positive eHMI effects. Information on intent and perception does not provide a significant higher positive effect.

The impact of message perspective in eHMIs is a another crucial aspect in improving the interaction between pedestrians and AVs. Research in this area investigates how the presentation of messages, either from the perspective of the AV or from the pedestrian, influences the perception and intention of the pedestrian. For example, when using text-based messages, studies show that the use of egocentric messages (from the perspective of the pedestrian) yield higher clarity scores than allocentric messages (from the perspective of the vehicle) and ambiguous messages (could be from either perspective) (Eisma et al., 2021). This indicates that people are better at interpreting messages relating to themselves. Another study, in which different eHMI concepts were compared based on a survey, showed that the use of textual messages were generally clearer and more persuasive than non-textual eHMIs, such as color-only eHMIs (Bazilinskyy, Dodou, and De Winter, 2019). Furthermore, confirming the result of the previous study, it found that the use of egocentric text messages are more persuasive than allocentric text messages. The downside of such egocentric text messages, however, could be that when multiple road users are encountered, it becomes unclear who the message is addressing. This could, for instance, cause a pedestrian to cross the road at an unsafe moment, thereby creating a dangerous situation.

Furthermore, the visibility of eHMIs plays a vital role in pedestrian-AV interaction. This could include changing the position of the interface on the vehicle. A study by Troel-Madec et al., 2019 conducted multiple experiments to investigate how well an eHMI can be observed by a pedestrian. In this experiment, the pedestrian needed to cross a road in front of a row of three vehicles. Results showed that placing the eHMI solely on the front of the vehicle means it only becomes clearly visible for the first car in line. For the cars further back in line, it becomes less visible with each position it moves back. In case of multiple cars in line, showcasing the eHMI on the side of the car makes it more visible. Therefore, solely showing the interface on the front of the car might not be ideal, especially in dense urban environments where it is quite possible to have traffic blocking the line of visibility.

Designing effective eHMIs also requires consideration of how different variables impact and interact with one another. Dey et al. (2020) researched all existing eHMIs documented in literature to develop a taxonomy aimed at assessing and comparing each one. This taxonomy serves as a guideline and checklist for evaluating and selecting a suitable eHMI design when developing an interface. The first general taxonomy dimensions explored are regarding the vehicle type and the target road user. These are important to identify since each target road user behaves differently in traffic, and thus has different needs and perceptions. Pedestrians, for example, tend to require visual modalities, however, their effectiveness depends on environmental and contextual factors (Dey et al., 2020). Highly complex and aesthetically pleasing visual displays might fail to communicate intent quickly enough in real-world traffic conditions. Furthermore, Dey et al. (2020) concluded that all forms of communication are categorized as either visual, auditory, haptic, body language or other forms of communication, meaning each eHMI has to adapt at least one of these forms of communication. Other important taxonomy dimensions that need to be considered when selecting an eHMI are color use, which only apply for visual eHMIs, message of communication in right-of-way negotiation, eHMI placement, number of displays, number of messages, communication dependence on distance and complexity of implementation (Dey et al., 2020). It becomes clear that there are many different aspects to take into consideration when selecting the appropriate interface, as not every design is suitable in every situation, making it a complex decision.

2.2 Cyclist-AV interaction

Now that the interaction between pedestrians and AVs is better understood, the interaction between cyclists and AVs can be analyzed to identify how cyclists' behaviour differs or compares to that of pedestrians. While the findings from pedestrian-AV studies can be useful and provide valuable insights, it may not all be directly applicable to cyclist-AV interactions. Cyclists behave differently than pedestrians, as they for instance move faster, have greater speed changes, differ in mobility and positioning on the road (Eriksson et al., 2019; Che et al., 2021). This leads to different interaction dynamics with AVs. Furthermore, cyclists' decision-making processes and safety perceptions can also differ from those of pedestrians. A study by Zhang et al. (2020) found that, when comparing driving, cycling, and walking near an AV, cycling was perceived as the least safe activity. This difference in perception can significantly influence how they respond to AVs.

While research on cyclist-AV interaction is considerably less advanced as that of pedestrian-AV interaction, recent studies have begun to delve into the complexities of cyclist behaviour. Similarly to the study on pedestrians' crossing behavior when interacting with AVs using VR by Velasco et al. (2019), the crossing intentions of cyclists can be investigated when interacting with AVs using VR. This was researched in a different study by Nuñez Velasco et al. (2020), in which a number of participants were shown videos of different crossing scenarios using VR glasses. The videos were shown from the perspective of a cyclist encountering either an AV or a conventional vehicle. The participants were asked what they would do in the given scenario. The main results indicate that the distance between the two road users and having the right-of-way are the most crucial factors in determining the cyclist's crossing intentions. When the distance decreases, the cyclist is more likely to adjust its speed, hinting at the cyclist feeling less safe. The vehicle speed as well as the vehicle type did not have a significant impact on the cyclist's intentions, therefore indicating that the participants did not perceive more risk when interacting with an AV compared to a conventional vehicle (Nuñez Velasco et al., 2020). This is different compared to the previous study by Velasco et al. (2019), in which the pedestrian would be less willing to cross when interacting with an AV. However, in both studies, a larger gap size between the two road users appears to increase the crossing intentions.

Another study applied a field experiment to investigate the risks resulting from the interaction between a cyclist and an AV, in which four different overtaking scenarios were tested, each with varying overtaking speed, overtaking distance and right-hand side objects (Oskina et al., 2023). In these scenarios, the AV has a following maneuver, in which it follows the cyclist, and then an overtaking maneuver, in which it overtakes the cyclist. One of the key findings is that, generally, when the AV is following the cyclist, no difference in behavior and trust is observed compared to manual driving. However, when overtaking the cyclist, participants feel less safe, increase their speed and reduce the distance to the curb (Oskina et al., 2023). Thus concluding, cyclists perceive less trust and more risk when interacting with an AV compared to a manual vehicle, in case of overtaking. Furthermore, the perceived risk is higher when the interaction time between AV and cyclist increases and when the overtaking distance is smaller.

Subsequent research has explored how eHMIs might support cyclist-AV interactions in traffic scenarios. Before asking the question which kind of eHMI is the most beneficial to the interaction between cyclists and AVs, the fundamental question if an eHMI is useful to support these interactions has to be answered, as this question has been largely neglected (Kaß et al., 2020). In this study a bicycle simulator was used to evaluate the behavior of cyclists in a number of different interaction scenarios with an AV. It showed that the use of an eHMI led to more effective and efficient crossing behavior of the cyclist, indicating that there certainly are benefits to using eHMIs (Kaß et al., 2020).

Lindner et al. (2022) investigated the interaction between cyclists and AVs with the use of a coupled driving simulator in a virtual environment. The cyclist and AV have to interact at different conflict points and can communicate with the another using a web application on mobile devices, which are used as HMIs. In those scenarios either the conventional traffic rules apply, the AV decides the traffic rules autonomously or the AV passenger decides the traffic rules. A number of simulation runs were executed with two participants each, one for the AV passenger and one for the cyclist, after which a questionnaire was filled out, including questions on safety perception. The results showed that the subjects rate the overall experience as positive, indicating that the use of a mobile device as HMI may serve as an effective communication tool.

Similar to pedestrian-AV interaction, selecting an appropriate eHMI design for cyclists' interaction with AVs requires complex considerations, as outlined by Dey et al. (2020). Cyclists present unique challenges due to their mobility, positioning and dynamics with other road users. Al-Taie et al. (2024) conducted a study in which three eHMIs are evaluated across several traffic scenarios using a VR cycling simulator. The findings showed that cyclists preferred colour-coded signals when communicating the AV's intentions, as these were easily understood. Furthermore, they preferred eHMIs using large surfaces on the vehicle and animations that make use of colour changes.

To conclude, the existing literature on the interaction between cyclists and AVs is still lacking, as there are significantly more studies done on the interaction between pedestrians and AVs. In specific, there is a lack of research exploring this dynamic within a VR environment and with the use of eHMIs as a communication tool. Therefore, there is a need for further investigation in this domain to fully understand and address the complexities of cyclist-AV interactions.

2.3 Traffic scenarios involving AVs

There are many different situations in which cyclists will encounter automated vehicles in day-to-day traffic, which all present unique challenges in ensuring safe interaction. Some require more communication between the participating road users than others. The first example of common traffic scenarios are intersections and road crossings, which can be defined as a junction where two or more roads meet or cross. It can, for example, consist of a four-way intersection, in which the roads cross over each other, a T-junction, in which the roads do not cross over each other, or in the form of a roundabout (Structural Guide, 2023). These intersections can be provided with stop signs or traffic lights to indicate the right-of-way. Otherwise, regular traffic rules apply to determine who has the right-of-way. However, when traffic signs or rules are ignored accidents happen (Retting, Weinstein, and Solomon, 2003). A study conducted by the National Highway Travel Safety Administration (NHTSA) showed that in 2020, 26% of the total bicycle fatalities occurred at intersections (Administration, 2022), highlighting the significant risks that these traffic situations bring for cyclists.

Another potentially dangerous situation between cyclists and AVs occurs when overtaking and passing the cyclist. In such situations the AV must ensure that they leave enough space for the cyclist when overtaking, and need to maintain a steady speed and predictable behaviour in order for safe passing (Brijs et al., 2022). However, when these conditions are not met, it can create hazardous situations. Studies have shown that more severe injuries of cyclists in overtaking collisions may result from motorised vehicles with higher velocities compared to in junction accidents, in which the vehicle often needs to slow down (McCarthy and Gilbert, 1996). Furthermore, overtaking collisions occur with larger vehicles as they tend to leave less space when passing the cyclist compared to normal cars (Walker, 2007).

In which of these scenarios, however, is communication helpful in assisting safe interaction between the cyclist and the vehicle, and therefore benefits from the use of eHMIs? When it comes to intersections and junctions, communication between the cyclist and vehicle is essential in signaling intentions, especially in unsignalized intersections (Mohammadi, Bianchi Piccinini, and Dozza, 2024). For traditional vehicles these can consist of eye contact, hand gestures, but also by the use of turn signals. However, in most ordinary intersections, standard traffic rules and signals apply, which dictate the right-of-way. In some cases even traffic lights are present to give clear instructions that both AV and cyclists follow. This means that the use of direct communication and thus eHMIs in such intersections might be helpful in improving interactions, but will probably not necessarily be needed to indicate who has the right-of-way (Clercq et al., 2019). In overtaking situations, vehicles are less able to communicate with cyclists as they come from behind, which means the cyclist is not likely to see them approach and thus interpret the intended communication by the vehicle (Wood et al., 2009). The vehicle needs to maintain a respectable speed and leave enough space for the cyclist to overtake in a safe manner. Communication might be helpful but it is not necessarily needed to safely pass (Wood et al., 2009).

One particular traffic scenario in which communication between VRUs and AVs is very important to ensure safe interaction, and thus potentially benefits from the use of eHMIs, is the concept of "shared space" (Li et al., 2021). A shared space area is often an urban environment in which the distinction between pedestrians and motorised vehicles is minimized by removing curbs, traffic signs, traffic signals and road markings (Moody and Melia, 2014). This enables all road users to share the same space without clearly defined rules that must be followed. Instead, it relies on the use of different forms of communication and social interactions between the road users (Wang et al., 2022). Therefore, the use of eHMIs in shared spaces could play a crucial role in effectively replacing traditional communication methods, helping AVs convey their intentions towards other road users, and thus potentially enhancing cyclist-AV interactions. Li et al. (2021) suggests that eHMIs can facilitate communication between AVs and VRUs, including cyclists, addressing challenges posed by the absence of a driver. It can thus be concluded that eHMIs are a promising solution to address the unique challenges posed by shared spaces and facilitate safe interactions between AVs and cyclists.

2.4 Discussion and conclusion

In conclusion, the current state of research on pedestrian-AV and cyclist-AV interactions have been analyzed, with a particular focus on the role of eHMIs in enhancing these dynamics. Utilizing VR experiments as a research method provides to be a useful tool for examining these VRU-AV interactions as they are cost-effective, flexible in scenario-development and most of all safe. Research on pedestrian-AV interactions has demonstrated several key findings. For instance, it was clear that the presence of designated zebra crossings significantly increases pedestrians willingness to cross. Furthermore, they experience reduced crossing intentions when they recognize the vehicle as an AV, possibly due to a mistrust in automation. This highlights a potential barrier to widespread acceptance of AVs and suggests the need to educate the general public to increase awareness and understanding of AV technology and its potential benefits. This can be done by providing clear information on how they operate and their safety features, but also by addressing possible concerns and misconceptions towards their safety and reliability. Another way of potentially increasing trust, is by integrating eHMIs into AVs as they enhance the communication towards pedestrians. Studies showed that eHMIs effectively capture pedestrians' attention towards AVs, possibly leading to safer and efficient interactions.

Although extensive research has been conducted on the interaction between pedestrians and AVs, the study of cyclist-AV interactions remains relatively insufficient. Recent studies have begun to delve into this dynamic, revealing important insights into safety perception and trust levels. For example, findings from field experiments and virtual experiments indicate that cyclists perceive less trust and a higher risk when interacting with an AV in comparison to a traditional vehicle, when being overtaken. The perceived risk is higher when the interaction time increases and the overtaking distance decreases. This raises the concern about the efficiency of current AV technology in accommodating the needs of cyclists and therefore highlights the need for further research in this area. Such research should address and resolve the unique challenges that cyclist-AV interactions present to improve the overall safety and comfort of cyclists on the road. When analyzing the crossing intentions of cyclists when interacting with AVs in a VR environment, it can be observed that the distance between them and having the right of way are the most influential factors in establishing cyclists' crossing intentions. The vehicle speed and vehicle type does not significantly influence cyclists' intentions.

When exploring VRU-AV interactions, it becomes clear that eHMIs play a vital role in enhancing these interactions and the communication between them. Studies have shown that the use of an eHMI leads to more effective and efficient behavior of other road users and increases their trust in AVs. Understanding aspects as the communication type, design and application is essential for developing eHMI designs that meet the informational needs of road users. In literature, a taxonomy has been created examining multiple dimensions and considerations that impact the effectiveness of an eHMI, which can be used as a checklist for selecting the right design when developing an interface. Other notable findings from literature indicate that message perspective and interface positioning can influence how eHMIs are perceived. However, research on the use of eHMIs in cyclist-AV interaction is still relatively underwhelming compared to pedestrian-AV interaction, especially when using VR as a research method. While eHMIs have been shown to improve communication with pedestrians, studies on their application in interactions with cyclists are sparse. There is a need for further research that focuses specifically on cyclists' preferences and responses to different types of eHMIs. Future studies could incorporate VR to create immersive and realistic experiments under controlled conditions to systematically analyze how cyclists' perceive, interpret and respond to various eHMI designs. For example, experiments can be conducted that evaluate and compare the effectiveness of visual, auditory and haptic signals. Other avenues of research could be the exploration of user preferences and acceptance of different eHMI designs or the use of multi-modal communication, in which different types of designs are combined to enhance communication.

Finally, among the various traffic scenarios in which cyclists and AVs interact, shared spaces present a unique challenge. In these particular environments, there are no traditional traffic rules and signs that indicate the right-of-way, making communication between road users even more essential. Therefore, these situations would benefit from the use of eHMIs to support communication between AV and cyclist by explicitly conveying the AV's intentions. As such, shared spaces offer a valuable context for future research. Studies should explore how different eHMIs impact cyclists' behaviour and perceptions, as exploring this domain could provide important insights for the development of AV systems.

2.5 Conceptual model

Based on the insights derived from the reviewed literature, it becomes evident that multiple factors influence the cyclist's crossing behaviour when interacting with AVs. To capture these relations and establish a theoretical foundation for this study, a conceptual model has been developed. The model is designed to define the crossing behaviour of cyclists and to analyze how it is affected by different variables, such as the personal characteristics of the cyclist and the eHMI type used in the interaction. Not all relations are investigated in this study. The most important relations, that are also analyzed in the VR experiment, are highlighted and a hypothesis is given on how each relation potentially impacts the crossing behaviour of cyclists. The conceptual model is shown in Figure 1, in which a green arrow indicates a positive relation between two variables, a red arrow indicates a negative relation between two variables, and a black arrow indicates an unknown relation between two variables or a relation that can be both positive and negative.

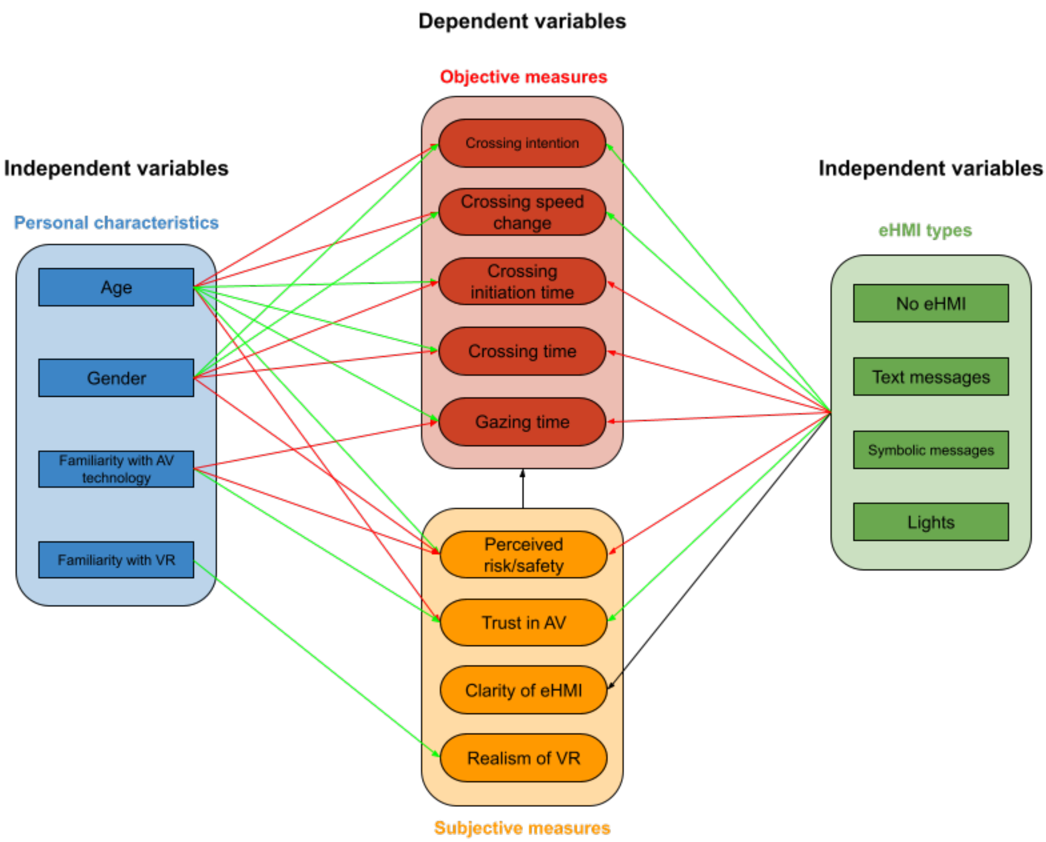


Figure 1: Conceptual model

2.5.1 Independent variables

The independent variables are the variables that influence the dependent variables in the model. In this study, they consist of the personal characteristics of the participants, indicated in blue, and the different types of eHMIs to be used in the VR experiment, indicated in green. They are independent as they are not influenced by any other variables and they can be manipulated and varied to investigate the effects on the dependent variables.

1. Personal characteristics

Age

The first personal characteristic that has an influence on the cyclists' crossing behaviour and attitude towards AVs is the age of the cyclist. A study by Holland and Hill (2007) on the effect of age and gender on crossing intentions of pedestrians in risky situations has shown that the intention to cross decreases with increasing age. This is likely the same for cyclists when encountering an AV, hence the negative relation in Figure 1. There are not many studies conducted on the influence of age on cyclists' crossing speed change, initiation time, crossing time and gazing time. However, a study found, for example, that older people tend to take a more cautious approach in traffic due to factors such as reduced physical agility and slower reaction times (Westerhuis, 2018). This means that they are likely to have lower crossing speed changes and higher crossing initiation times compared to younger people. Furthermore, a study by Uetake and Shimoda (2014) analyzed the gazing behaviour of young and elderly cyclists. The findings indicated that elderly cyclists took a more cautious approach and needed longer gazing times compared to younger individuals. This suggests that when interacting with an AV, their ability to quickly interpret the vehicle's intentions may be reduced.

Gender

Another characteristic that can influence the crossing behaviour of cyclists is gender. To understand whether a relation is positive or negative, first a default gender needs to be set as gender is not a number like age is. The default gender in this model is male. This means, for example, that when the crossing intentions are higher for males compared to females, it will have a positive relation and is thus indicated with a green arrow. If the crossing intentions would be higher for females compared to males, it would be a negative relation, thus indicated by a red arrow.

Holland and Hill (2007) found that female pedestrians are less likely to cross and perceive more risk compared to men. These relations are likely to be the same for cyclists. Since men are more likely to partake in risk-taking behaviour, men may also tend to have higher crossing speed changes, while women may tend to have more cautious behaviour (Cobey et al., 2013). The crossing initiation time and crossing time therefore is probably also higher for women compared to men.

Familiarity with AV technology

The level of familiarity with AV technology also has an influence on the crossing behaviour of cyclists when interacting with an AV. When the cyclist is aware of how the AV functions and understands the safety measures and protocols of the AV, they might feel more comfortable and more trustworthy towards the AV. When the trust is higher in the AV, studies have shown that the attitude towards AV is more positive, therefore also lowering the perceived risk when interacting with the AV (Zhang et al., 2019). Lastly, the gazing time towards the AV will likely decrease when the cyclist is more aware of how the AV operates and communicates, as the vehicle's intentions might be more clear.

Familiarity with VR

The last personal characteristic of the cyclist that influences their crossing behaviour, is the level of familiarity with VR technology. This has an influence on how the participant perceive the realism of the VR environment and experiment. When the familiarity is higher, the participant is more likely to appreciate and recognize the realism of the VR environment, as they understand the capabilities as well as the limitations of the VR technology (Nam, Lee, and Kim, 2023). Therefore, they are more likely to interpret and engage with the virtual environment effectively.

2. eHMI types

The next set of independent variables that influence the crossing behaviour of the cyclist are the eHMI types used by the AV in the traffic situation. They consist of the following design types:

- No eHMI
- Text messages
- Symbolic messages
- Lights

What the exact eHMI designs of each type looks like is explained in further detail in Chapter 3. To understand the impact each type has on the crossing behaviour of the cyclist, first having any eHMI will be compared with having no eHMI. The relations shown in Figure 1, therefore highlight whether having any eHMI has a positive or negative impact on a certain dependent variable, compared to having no eHMI. Kaß et al. (2020) conducted a study on the importance of eHMIs in VRU-AV interaction using a bicycle simulator. The results showed that the use of any eHMI leads to more effective and efficient behaviour of the cyclist, indicating higher crossing intentions and lower crossing initiation times. Gazing time towards the AV is likely to be lower when an eHMI is present, as the intentions of the AV is quicker understood (Liu et al., 2020). Further studies indicate that the presence of an eHMI leads to a higher level of trust and understanding of the AV (Ferenchak and Shafique, 2022), which means that the perceived risk is also lower. The clarity of the eHMI depends on the type and design of the interface, and therefore has an unknown relation.

2.5.2 Dependent variables

The dependent variables in the model are the variables that are influenced by the independent variables, and consist of objective and subjective measures. The objective measures are indicated in red and consist of the physical behaviour of the cyclist during the interaction with the AV. These variables can be quantified and measured during the actual VR experiment. The subjective measures are indicated in orange and consist of the intention and attitudes towards the AV and the eHMI used in the interaction. The latter rely more on the human judgement, personal opinions and perspective of the cyclist. These variables cannot be quantified but can be scored in the post-experiment questionnaire. The subjective measures also have an impact on the actual behaviour of the cyclist. For example, if the cyclist perceives more risk in a particular situation, they might have lower crossing intentions.

1. Objective measures

Crossing intention

The first objective measure that indicates the crossing behaviour of the cyclist is its crossing intention. This variable is defined as to whether the cyclist decides to cross or to stop for the AV. It is therefore a binary variable, the cyclist either crosses before the AV or after the AV. Therefore the value is either equal to one or zero, respectively.

Crossing speed change

The next objective measure is the crossing speed change, or crossing acceleration. It is defined as the maximum difference in speed after taking action when the eHMI is shown. The cyclist can either decide to keep the same speed, speed up, slow down or even come to a full stop.

Crossing initiation time

The crossing initiation time is defined as the time it takes for the cyclist to take action after the eHMI is shown. When taking action the cyclist changes its speed, either slowing down, speeding up or coming to a full stop.

Crossing time

The next objective measure that defines the crossing behaviour of cyclists, is the crossing time. This indicates the time it takes the cyclist to complete the crossing maneuver after the eHMI is shown.

Gazing time

The last objective measure is the gazing time of the cyclist towards the AV and in specific the eHMI. It measures or estimates the total time that the cyclist is looking at the direction of the AV.

2. Subjective measures

Perceived risk/safety

The first subjective measure that indicates the attitudes of the cyclist towards the AV, is the perceived risk of the cyclist. It is the subjective judgement of the cyclist on the potential danger they believe they might encounter in a certain situation. If the perceived risk is higher, the cyclist feels less safe and will likely have lower crossing intentions.

Trust in AV

Another subjective measure is the trust of the cyclist in the AV. This refers to the cyclist confidence and trust in the AV's ability to act safely and predictably when interacting with each other. When there is little trust in the AV, the cyclist will likely have lower crossing intentions and adjust its speed accordingly.

Clarity of eHMI

The third subjective measure is the clarity of the external interface and refers to how effectively it is able to communicate the AV's intention to the cyclist. If the eHMI is not clear, the cyclist might not be able to properly understand the AV's actions which results in a different crossing behaviour. The clarity of the interface can for example depend on the visibility, simplicity and intuitiveness of the eHMI.

Realism of VR

The last subjective measure is the realism of the VR environment. This entails how accurately the VR environment is able to represent real-life implications. A highly immersive and realistic environment means that the results of the simulation are also applicable to real-world situations.

2.5.3 Hypotheses

In Figure 2, the condensed conceptual model is presented, highlighting only the relations that are directly investigated in this study. As shown, the personal characteristics are not analyzed in the VR experiment. The reason for excluding the impact of age and gender is based on the fact that they have already been researched in multiple studies and can largely be explained by physical and cognitive differences. Additionally, incorporating the level of familiarity with AV and VR technology might be pose methodological challenges, as it is difficult to measure accurately and reliably. Including such variables could also increase the complexity of the experimental setup without aligning with the central aim of this study. The primary focus of this study is to examine the effect of the different types of eHMIs on cyclists' crossing behaviour, rather than to explore the influence of personal characteristics. Nevertheless, data on participants' age, gender, and familiarity with AV and VR technology are collected. While not analyzed in the current study, this data offers valuable opportunities for future research into the role of individual differences in shaping cyclist-AV interactions.

Based on the literature reviewed on VRU-AV interactions, it is expected that the presence of any eHMI leads to a higher crossing intention, speed change and trust in the AV, and a lower crossing (initiation) time, gazing time and perceived risk. However, the specific design of the eHMI plays a crucial role in the effectiveness of the eHMI at conveying its intentions.

It is expected that text messages will have the most positive impact on the crossing intentions of the participants, as they are generally clearer and more persuasive than non-textual eHMIs (Bazilinskyy, Dodou, and De Winter, 2019). Symbolic messages are expected to have a moderately high effect on crossing intentions, and can effectively convey the vehicle's intent when the symbols are intuitive (Habibovic et al., 2022). Light-based eHMIs may have a weaker effect due to potential ambiguity to cyclists without prior learning (Hensch et al., 2019). Such eHMIs require some level of familiarization before cyclists can accurately interpret their meaning.

This indicates that text messages are likely to have higher clarity ratings and require less gazing time than the other non-textual eHMIs. Also, the crossing initiation time and crossing time is expected to be the lowest for textual eHMIs, since their clarity enables faster decision-making (Bazilinskyy, Dodou, and De Winter, 2019). Symbolic and light-based eHMIs may require more time to interpret the signal's meaning (Clercq et al., 2019). Textual eHMIs are expected to generate the lowest perceived risk and highest trust in the AV, for the same reasoning as before. Overall, textual eHMIs are expected to convey the clearest message, without any need for prior learning.

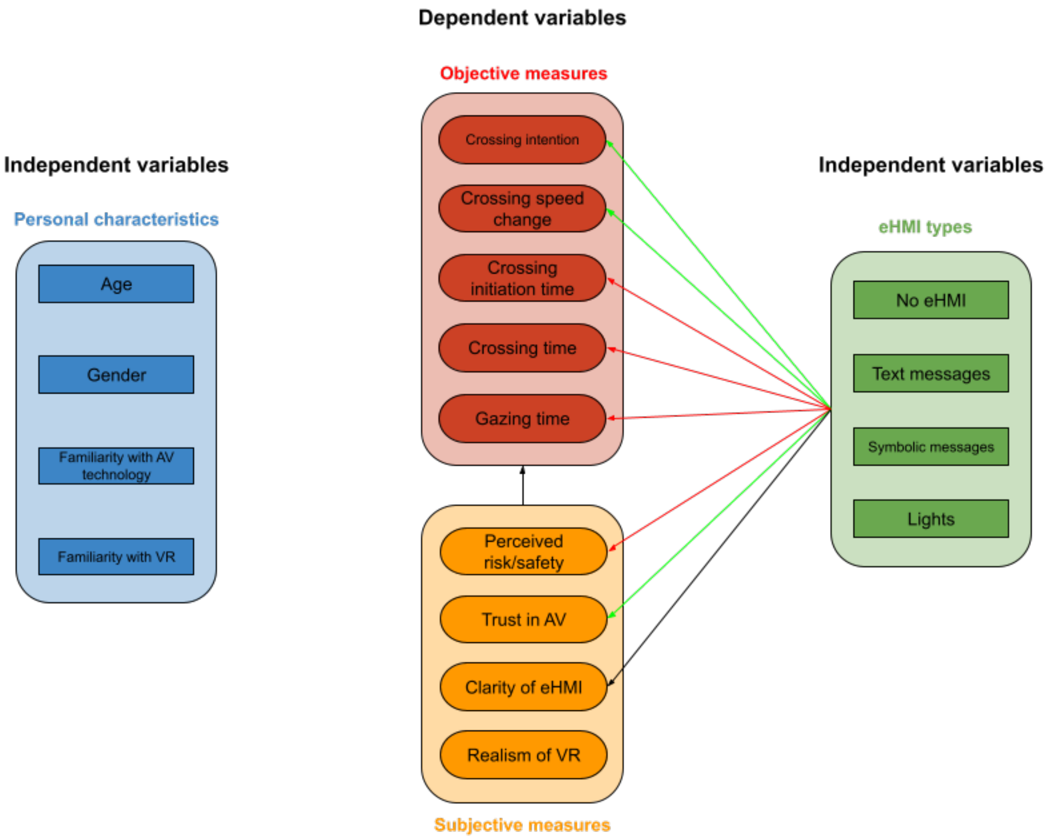


Figure 2: Condensed conceptual model

3 Methodology

In this section, the methodology of the research is explained in detail, as well as the complete procedure of the VR experiment. It provides an overview of the experiment design, in which the traffic scenarios and eHMI designs are explained, and the hardware and software that are used in the experiment. Furthermore, this chapter presents the contents of the post-experiment questionnaire, as well as the methods used to collect and analyze the experimental data.

3.1 Experiment design

To investigate cyclists' crossing behaviour when interacting with an AV, their perceptions on safety and trust, and their preferences regarding eHMI design, a VR experiment is conducted. The experiment involves a number of participants who engage in the role of a cyclist using a VR bicycle simulator. They are equipped with a VR headset to be fully immersed in the virtual environment. In the experiment, they encounter an AV in several traffic scenarios to observe how their behaviour varies when interacting with different eHMIs.

3.1.1 VR environment

The virtual environment is created in Unreal Engine 5 and represents a fictional shared space area in an urban setting. The environment is based on a template of a city area and is adjusted accordingly to represent a shared space. Within the shared space, no typical traffic rules apply such as right-of-way rules. In addition, it does not include any additional traffic signs or lights, curbs, sidewalks, and lane indications. The idea of a shared space is to have all modes share the same road space in order to encourage negotiation of priority using eye contact and non-verbal communication. Figure 3 shows images of the shared space area that has been created in Unreal Engine. The environment consists of four roads intersecting, creating a square in the middle in which different road users have to interact with one another. To represent a realistic urban setting, the environment is filled with buildings and urban props such as a fountain, benches, parked cars and bicycles, and outdoor seating of restaurants and cafes. The environment also features various animated virtual bystanders to create a more lively atmosphere.

(a) View of the starting position of the cyclist

(b) View of the square

(c) View of the square from another direction

Figure 3: Screenshots of the VR environment.

3.1.2 Participants' task

In the VR experiment, the participants take on the role of the cyclist and perform a series of scenarios. Once the first scenario begins, they are instructed to start cycling from the start to the end point. The route of the cyclist is always a straight line, so no turning is needed. Along the route, they will cross paths with an AV that displays one of the eHMI types and either yields to the cyclist or continues driving. The cyclist's task is to pay close attention to the AV's behaviour and any signals presented via the eHMI. Based on their perceptions, they must respond to the AV. This could be by either stopping or slowing down and letting the AV cross, or by choosing to cross before the AV. Afterwards, they continue cycling towards the end point, which is clearly indicated within the virtual environment. Upon reaching the end point, the next scenario automatically starts, and the cyclist is asked to once again navigate the route while observing and responding to the AV. This process is repeated until all scenarios are completed, which finishes the VR experiment.

3.1.3 Scenarios

The experiment consists of a total of 11 different scenarios that each of the participants are asked to perform. In each scenario, the path of the cyclist is the same. The scenarios are divided into two groups: primary scenarios and additional "confusing" scenarios. The primary scenarios are the core focus of the data collection in this experiment and thus consist of the only scenarios from which data are required. They consist of 8 scenarios, in which the AV always approaches the cyclist from the right-hand side. In Table 1, the primary scenarios are written out.

Table 1: Primary scenarios

Scenario	Direction of the AV	eHMI design	Yielding
Scenario 1	Right-hand side	No eHMI	Yes
Scenario 2	Right-hand side	No eHMI	No
Scenario 3	Right-hand side	Textual messages	Yes
Scenario 4	Right-hand side	Textual messages	No
Scenario 5	Right-hand side	Symbolic messages	Yes
Scenario 6	Right-hand side	Symbolic messages	No
Scenario 7	Right-hand side	Lights	Yes
Scenario 8	Right-hand side	Lights	No

The variables that change are the eHMI design and whether the AV yields to the cyclist or not. For each eHMI design, there is one scenario in which the AV yields to the cyclist and one scenario in which it does not yield to the cyclist. By keeping the direction from which the AV approaches the cyclist constant, the influence of the vehicle's direction on the cyclist's crossing behaviour is mitigated. This allows for a clearer analysis of the primary variable of interest, which is the eHMI design. It ensures that any observed differences in cyclist behaviour can be attributed primarily to the eHMI rather than external factors such as vehicle direction.

Figure 4 shows the starting/ending position and path of the cyclist and the AV in these scenarios. The point O is the intersection point between the path of the cyclist and the path of the AV. The starting position of the cyclist is at 75 meters before the intersection point, indicated by location A, the end point is at 50 metres after the intersection point, indicated by location B. When the cyclist crosses location E, at 58 meters before the intersection, the AV starts driving. The AV starts at 35 meters before the intersection point, at location C, and will approach the intersection at 15 km/h. The end point of the AV is 50 meters after the intersection at location D. The yellow line indicates the path of the cyclist, and the blue line indicates the path of the AV.

To determine at which distance from the cyclist the eHMI should be displayed and the AV should stop (in case of yielding), three different gap sizes are tested. From Nuñez Velasco et al., 2020, the three different gap sizes to be tested are determined: 2 s, 3 s and 4 s. With a speed of 15 km/h, this can be converted into the distance from the cyclist: 8.33 m, 12.5 m and 16,67 m. The distance between the AV and the cyclist can be calculated in real time using their coordinates in Equation 1. This equation is used in Unreal Engine to make sure that the AV stops when the distance between the two road users becomes smaller than the gap size.

$$d = \sqrt{(x_{AV} - x_{cyclist})^2 + (y_{AV} - y_{cyclist})^2} \tag{1}$$

After testing all three gap sizes, it can be concluded that a gap size of 4 s (or 16.67 m) generates the most realistic interaction between the AV and the cyclist. Therefore, this gap size is used in the experiment. Thus, in case the AV yields to the cyclist, at 16.67 meters from the cyclist, the AV stops. In case the AV does not yield to the cyclist, the AV continues to drive at 15 km/h.

This is displayed in Figure 4, where nodes A' and C' indicate the position of the cyclist and the AV, respectively, were the distance between them is 16.67 meters.

The distance at which the AV shows the eHMI, is calculated slightly differently. This is the distance between the AV and the intersection point of the two paths, which is at a distance of 16.67 m. This is indicated by point F in Figure 4. The reason for this, is that the eHMI should be shown somewhat before the AV comes to a stop, in order for the cyclist to understand its intention and thus behave accordingly.

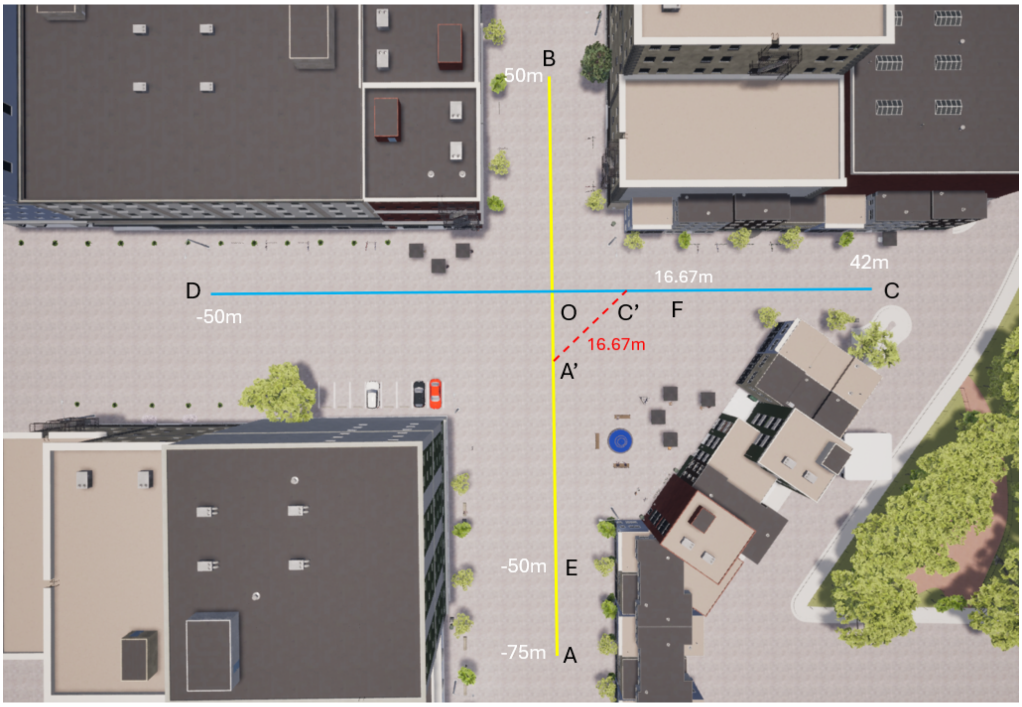


Figure 4: Top view of the experiment environment when AV approaches from RHS

Then there is a set of additional "confusing" scenarios, which consist of 3 scenarios and aim to reduce bias in the participants' responses. These scenarios include two scenarios in which the AV approaches the cyclist from the left-hand side (one in which the AV yields to the cyclist and one in which the AV does not yield to the cyclist) and one scenario in which the AV will approach the cyclist from straight ahead. Table 2 highlights the three scenarios.

Table 2: "Confusing" scenarios

Scenario	Direction of the AV	eHMI design	Yielding
Scenario 9	Left-hand side	Random	Yes
Scenario 10	Left-hand side	Random	No
Scenario 11	Straight ahead	No eHMI	No

In the scenario 11, there is no conflict between the two as they do not cross paths, so yielding is not required of the AV. Therefore, there is also no need for an eHMI to communicate with the cyclist, so the eHMI design is "No eHMI". The "confusing" set of scenarios is introduced to prevent participants from predicting the direction from which the AV approaches, which could influence their behaviour. Therefore, they ensure that the participants' responses are not influenced by learned patterns throughout the experiment, which improves the reliability of the data. These scenarios are only meant to "confuse" the participants and are not included in the final analysis of the data.

In Figure 5, the starting/ending position and the path of the cyclist and the AV in the first two "confusing" scenarios are shown. The starting position, ending position and path of the cyclist remain the same as in the primary scenarios. The starting and ending positions of the AV are different, and are again indicated by locations C (starting position) and D (ending position), however, the distances from the intersection point remain the same. Furthermore, the distance from the cyclist at which the AV stops and shows its eHMI when yielding the cyclist also remains the same as in the primary scenarios.

Figure 5: Top view of the experiment environment when AV approaches from LHS

Figure 6 shows the starting/ending positions and the path of the cyclist and the AV in the scenario 11. In this case, the AV comes head on the cyclist and therefore does not cross paths, but instead passes the cyclist parallel to its path. The starting and ending position of the AV have thus changed compared to the rest of the scenarios, and are again indicated with location C and D respectively. The distances remain the same.

Figure 6: Top view of the experiment environment when AV approaches head on

As indicated in Table 2, the eHMI designs of the LHS scenarios are randomly selected. The selection for each scenario is the same for every participant. The order of the scenarios is also randomized. First, the order of the primary scenarios is randomized within the set. Then, the three "confusing" scenarios are randomized within the set and are interspersed between the primary scenarios. This prevents the participants from being able to have certain expectations by introducing an element of unpredictability. The order of the scenarios again remain the same for each participant, which means every participant has the same set and order of scenarios that are tested. This leads to the final set of scenarios shown in Table 3.

Table 3: Final set of scenarios

Scenario	Direction of the AV	eHMI design	Yielding
Scenario 1	Right-hand side	Lights	No
Scenario 2	Right-hand side	Symbolic messages	Yes
Scenario 3	Left-hand side	Textual messages	Yes
Scenario 4	Right-hand side	No eHMI	No
Scenario 5	Right-hand side	Textual messages	Yes
Scenario 6	Straight ahead	No eHMI	No
Scenario 7	Right-hand side	Symbolic messages	No
Scenario 8	Right-hand side	Textual messages	No
Scenario 9	Left-hand side	Lights	No
Scenario 10	Right-hand side	No eHMI	Yes
Scenario 11	Right-hand side	Lights	Yes

3.1.4 eHMI designs

There are four different types of eHMIs that are tested in the VR experiment. Each eHMI will have the same placement on the vehicle, namely on the roof of the vehicle, which is a typical location of eHMIs on AVs (Eisma et al., 2021).

No eHMI
The first eHMI type is "no eHMI". Both for yielding to and not yielding to the cyclist, the eHMI is the same and does not show any display on the interface of the AV, as can be seen in Figure 7.

Figure 7: No eHMI design

Textual messages
The second eHMI consists of textual messages. When yielding to the cyclist the interface on the AV says "CYCLE", and when not yielding to the cyclist the interface says "NO CYCLE". Both designs are shown in Figure 8. The text will be displayed on three different directions on the interface, one at the front and two at the sides (one per side).

(a) Text shown when yielding to the cyclist

(b) Text shown when not yielding to the cyclist

Figure 8: eHMI designs of textual messages

Symbolic messages
Another eHMI design consists of symbolic messages. If the AV's intention is to yield to the cyclist, the interface shows a symbol of a cyclist to indicate that the cyclist can cross. If the AV's intention is to not yield to the cyclist, the interface shows a cross symbol to indicate that the cyclist has to stop. The designs in Unreal Engine are shown in Figure 9. Again, the symbols will be displayed on three directions on the interface.


(a) Symbol shown when yielding to the cyclist


(b) Symbol shown when not yielding to the cyclist

Figure 9: eHMI designs of symbolic messages

Lights
The last eHMI design consists of lights with different colors to indicate the AV's intention. When yielding to the cyclist, the lights of the eHMI turn green; when not yielding, the lights will turn red. Both designs are shown in Figure 10.

(a) Green lights when yielding to the cyclist

(b) Red lights when not yielding to the cyclist

Figure 10: eHMI designs of lights interface

3.2 Hardware and Software

The experiment utilizes a VR bicycle simulator to create an immersive and realistic cycling simulation, which is developed by the Mobility in eXtended Reality (MXR) Lab, in the department of Transport & Planning at TU Delft. For the bike simulator, a regular bicycle has been used that is mounted on a Tacx Flow Smart trainer. The Tacx trainer is equipped with a sensor that tracks the movement and speed of the bike. The bicycle setup can be viewed in Figure 11. Participants also need to wear an HTC Pro Eye VR headset, with which they are immersed in the virtual environment. The headset is able to track the head and eye movements of the participants. Both the bicycle simulator and the VR headset are connected to a high-end PC to ensure smooth operation.

(a) Setup of the bicycle simulator

(b) Tacx Flow Smart trainer and sensor

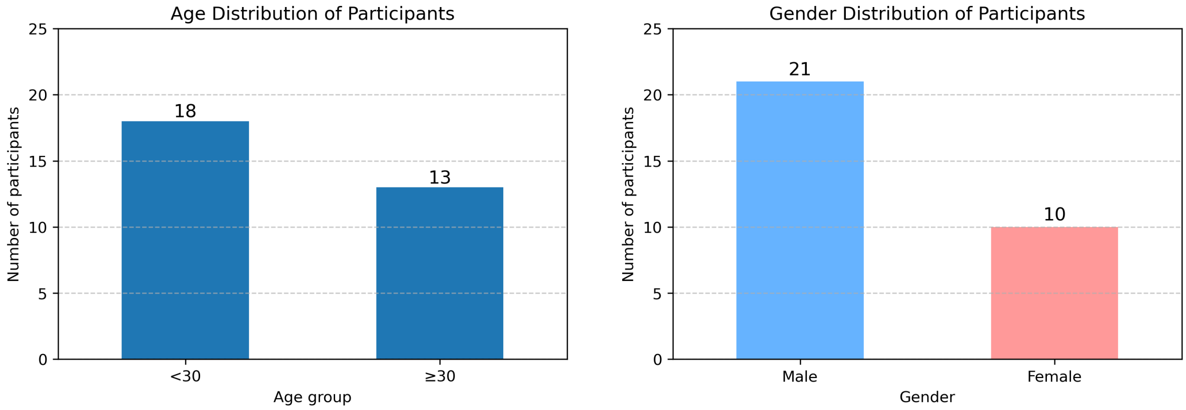
Figure 11: Bicycle setup for the VR experiment

Furthermore, a variety of software tools have been used to perform this research. The city environment was initially developed using a template in RoadRunner, which is an interactive editor that lets you create 3D scenes for simulating automated driving systems. The environment was then further developed and finalized in Unreal Engine 5, in which also the eHMI designs and movements of the AV were developed to create the different scenarios to be tested. SteamVR was then used in combination with Unreal Engine to enable virtual reality simulation. The data sets that were collected from the experiments were saved as CSV files. Finally, Microsoft

Forms was used to design and conduct the online post-experiment questionnaires, which allows for efficient collection of the participants' answers.

3.3 Participants

To perform the VR experiment, a total of 31 participants are recruited, of which 21 males and 10 females. The participants mainly consist of students at the TU Delft and are recruited through social media and posters around the campus. Another way the participants are recruited is through personal connections. There are no specific requirements for the age of the participants, only that they are at least 18 years old. Figure 12a indicates the age distribution of the participants. As can be seen, there are 18 individuals that are below 30 years old, and 13 participants that are 30 or above. The gender distribution of the participants is presented in Figure 12b. For the experiment, 21 male participants are recruited and 10 female participants.

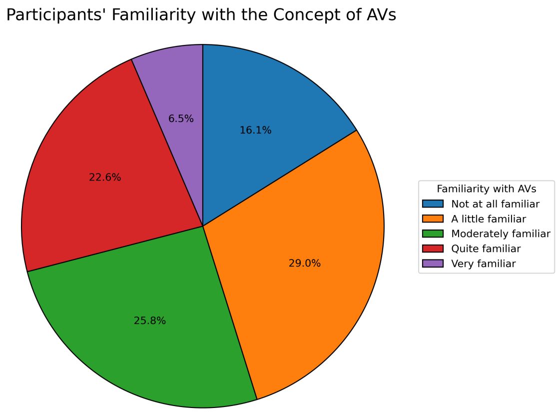


(a) Age distribution (b) Gender distribution

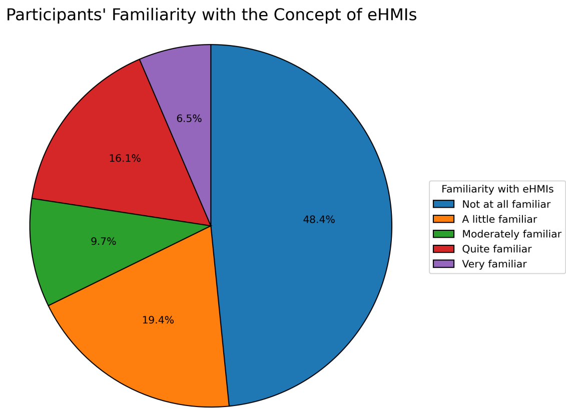
Figure 12: Age and gender distribution of the participants of the VR experiment

The participants' familiarity with the concept of both AV and eHMIs is indicated in 13. The distribution among the participants regarding the concept of AVs is quite even. 29.0% of the participants are a little familiar, 25.8% are moderately familiar and 22.6% are quite familiar, making up around three quarters combined. Only 16.3% of the participants are not at all familiar with AVs, and even less are an expert on the concept of AVs, with only 6.5%.

When it comes to the concept of eHMIs, the results suggest that the participants are considerably less familiar. Almost half of the group of participants are not at all familiar with the concept of eHMIs, with 48.4%. 19.4% are a little familiar, 9.7% are moderately familiar and 16.4% are quite familiar. Only 6.5% of the participants is an expert on the subject.



(a) Familiarity with AVs

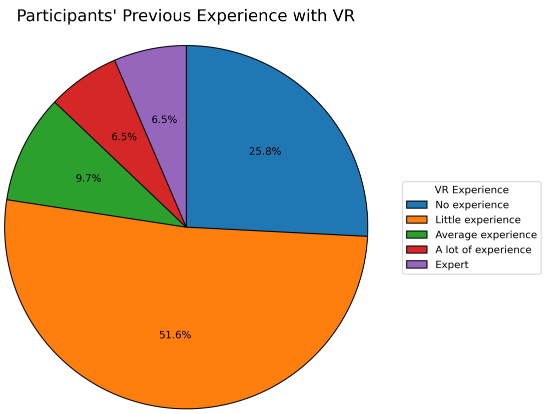


(b) Familiarity with eHMIs

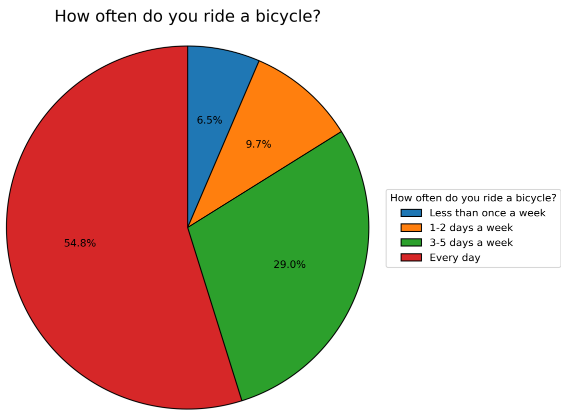
Figure 13: Participants' familiarity with the concepts of AVs and eHMIs

In Figure 14a, the participants' previous experience with VR is presented. The results indicate that around a quarter of the participants has no experience with VR, accounting for 25.8%, and more than half has little experience with VR, accounting for 51.6%. Then, 9.7% of the participants has average experience with VR. The last two categories, which consist of having a lot of experience and being an expert, account for the same percentage, with 6.5%.

Figure 14b shows how often the participants ride a bicycle. More than half of the participants ride a bicycle every day (54.8%) and almost a third rides it 3-5 days a week (29.0%). Only 9.7% rides a bicycle 1-2 days a week and 6.5% less than once a week.



(a) Experience with VR



(b) Experience with riding a bicycle

Figure 14: Participants' previous experience with VR and riding a bicycle

3.4 Procedure

The experimental procedure looks like the following:

1. Introduction: In this stage, the participants are given a written instruction of the experiment, including the complete experimental procedure and an explanation on AV technology, the use of eHMIs and the VR environment in which the experiment is conducted.

The participants are also asked to sign an informed consent form, after which they are still able to withdraw at any time during the experiment.

2. Familiarization: After the introduction is completed, the participants get a chance to familiarize with the VR equipment and bicycle simulator. In a simple VR environment without any other road users, they are able to test out the bicycle simulator. This will help them get used to the performance of the bicycle as well as getting used to wearing the VR headset.

   If participants experience any motion sickness, they are allowed to take a break and decide whether they want to continue the experiment.

3. VR experiment: When the participants feel comfortable with the VR equipment and the bicycle simulator, the actual experiment is conducted. The experiment is conducted as explained earlier in this section, following the set and order of the scenarios that are required to be tested by each participant. Once a scenario is started, the participant is asked to start cycling. When the participant reaches the end point, the scenario is stopped and the next scenario is started. This process is repeated for the whole set of scenarios explained in Table 3.

   The participant is checked multiple times throughout the experiment whether they are not feeling well or experience any sign of nausea, dizziness or other discomfort. The experiment is only continued when the participant feels comfortable to do so. Otherwise the participant is taken out of the experiment. The participant them-self is also able to withdraw from the experiment at any time.

4. Post-experiment questionnaire: Right after the experiment has been conducted, the participants are asked to fill in an online post-experiment questionnaire on a desktop PC. The specific parts of which the questionnaire consists are explained in more detail in the next subsection.

3.5 Data collection and analysis

To be able to draw conclusions on the behavior of the participants while interacting with different eHMIs, specific data is collected and analyzed. This data is collected from both the VR experiment itself as the post-experiment questionnaire. During the VR experiment, there are several data points that are collected per participant and per scenario. First of all, the timestamp is recorded during the whole duration of a scenario. For each timestamp, the bicycle position (X, Y, Z), head position (X, Y, Z) and head movement (roll, yaw, pitch) is recorded. Additionally, the focus point (X, Y, Z) and the focused object are recorded. The latter indicates which object within the virtual environment the participant is directly looking at. Finally, the bicycle speed, vehicle position (X, Y, Z) and vehicle speed are recorded. All the data is stored per participant and per scenario in CSV files.

These data points can then be used to determine the cyclist's crossing behaviour. As explained in Section 2.5, the crossing behaviour consists of multiple objective measures. These measures are indicated again in Table 4, in which is also highlighted how each measure can be calculated, and what variables are needed to do so.

Table 4: Data analysis summary

Measure [unit]	**Variables needed**	**Calculation**
Crossing initiation time [s]	1. Timestamp at which eHMI is shown 2. Timestamp at which cyclist takes action	= Variable 2 - Variable 1
Crossing time [s]	1. Timestamp at which cyclist takes action 2. Timestamp at which crossing maneuver is finished	= Variable 2 - Variable 1
Speed change [m/s^2]	1. Maximum acceleration/deceleration rate after eHMI is shown	= Variable 1
Gazing time [°]	1. Total cumulative yaw changes after eHMI is shown	= Variable 1
Crossing intention [-]	1. Timestamp at which cyclist reaches intersection point 2. Timestamp at which AV reaches intersection point	If Variable 1 < Variable 2, value = 1 If Variable 1 > Variable 2, value = 0

3.5.1 Crossing initiation time

The first objective measure that needs to be determined is the crossing initiation time. It is defined by the time it takes the cyclist to take action from the moment the eHMI is shown. Taking action can consist of either speeding up or slowing down in reaction to the eHMI that is displayed. The cyclist is considered to have taken action when their speed changes beyond a predefined threshold within a specific time window. To determine this threshold and time window, the average speed distribution of the participants can be used, displayed in Figure 15. As can be seen, after the eHMI is shown (at around 7 seconds), all speed distributions make a jump or drop of at least 3 km/h. These jumps/drops all happen within a time gap of around 3 seconds after the eHMI is shown. Therefore, the speed threshold and the time window needed to determine the crossing initiation time is set at 3 km/h and 3 seconds respectively.

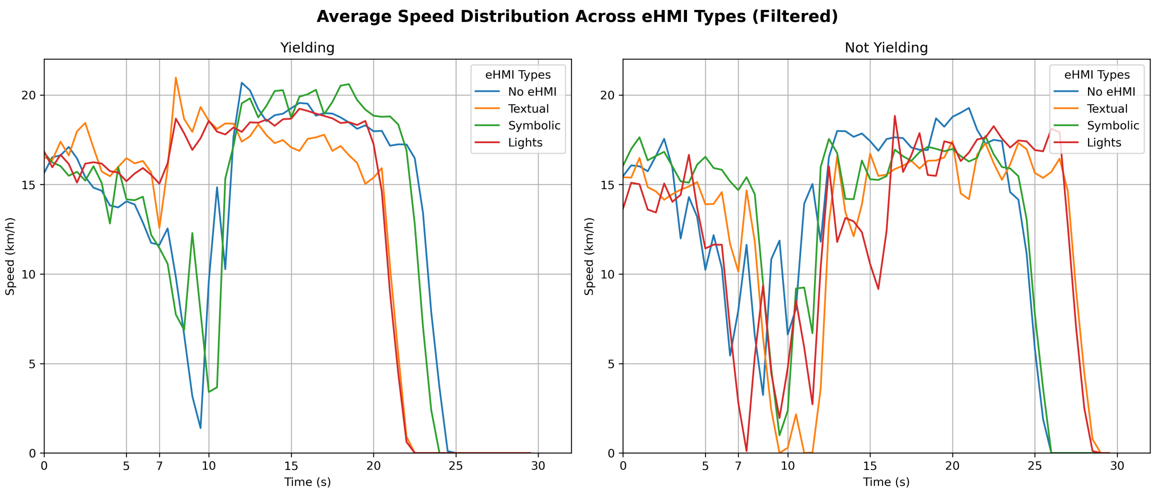


Figure 15: Average speed distribution per eHMI

To calculate the crossing initiation time, two key timestamps are needed. The first, is the timestamp at which the eHMI is shown, and the second is the timestamp at which the cyclist takes action (determined using the explained thresholds). By subtracting the two, the crossing initiation time can be determined.

The crossing initiation time is essential in evaluating the clarity and effectiveness of the eHMI. A longer initiation time indicates that the cyclist needs more time to understand the AV's intention, and thus the eHMI may be unclear. On the other hand, a shorter initiation time indicates that the eHMI is easily understood, allowing the cylcist to make quicker decisions.

3.5.2 Crossing time

The crossing time is then defined as the time it takes the cyclist to complete the crossing maneuver. To calculate this variable, two timestamps are needed. One is the timestamp at which the cyclist takes action, as previously defined, and the other is the timestamp at which the crossing maneuver is completed. This moment is defined as the point at which the cyclist reaches a position of 5 meters beyond the intersection point. The reason for selecting this specific point and not the end point of the scenario to determine the crossing time, is because the participants often decide to abruptly change their speed near the end of a scenario, making the data unreliable and inconsistent. By subtracting the two timestamps, the crossing time can be determined.

The crossing time is an important variable to assess the cyclist's decision-making and trust in the AV. A higher crossing time can indicate that there is little trust in the AV and its intentions, indicating an uncertainty or hesitation of the cyclist. If there is a shorter crossing time, it can suggest that the cyclist quickly understands the AV's intentions and also trusts its actions, allowing them to cross without delay.

3.5.3 Speed change

The next variable that is determined is the crossing speed change. This captures how abruptly the cyclist accelerates or decelerates in response to the eHMI. It is calculated by taking the maximum acceleration rate within a predefined time window after the eHMI is shown. The time window is again determined by analyzing the average speed distribution of the cyclists, shown in Figure 15. It can be observed that the largest changes in the speed distributions occur within a range of around 3 seconds after the eHMI is shown. Therefore, the same time window will be used as for the crossing initiation time, thus it will be set to 3 seconds.

This measure helps to assess the cyclist's level of urgency and perceived risk. A higher speed change means that the cyclist needs to intervene more abruptly, indicating more urgency to stop or accelerate, and thus more perceived risk. The cyclist might not have fully understood what the AV's intentions are, leading to an uncertainty in its actions. If for example, the cyclist has to suddenly brake hard, it may indicate a hesitation or late realization of the AV's intentions. If there is a gradual speed change, it suggests that the cyclist immediately understands the eHMI and the intentions of the AV, and they can anticipate the AV's actions without having to make sudden adjustments.

3.5.4 Gazing time

The gazing time is determined by analyzing the total cumulative change in the yaw angle of the participants' head after the eHMI is shown. During the experiments, the head roll, yaw and pitch of the participants are recorded. By analyzing how much the head rotated horizontally (yaw) over time, an estimation can be made on the duration of visual attention directed towards the AV. This is captured by the cumulative yaw changes. A larger value for the cumulative yaw changes indicates longer or more frequent gaze shifts, which means that the participants is likely to be spending more time looking towards the AV.

The gazing time can be a useful measure to determine the clarity and intuitiveness of the eHMI.

If the gazing time is high, it means the cyclist needs a lot of time to interpret the eHMI's message and the AV's intentions. Therefore, the eHMI might be considered to be unclear. For a shorter gazing time, the cyclist immediately understands the eHMI and the AV's intention. By comparing gazing times across different eHMI designs, it is possible to evaluate which design is the most intuitive.

3.5.5 Crossing intention

The last measure that needs to be determined is the crossing intention, which indicates whether the cyclist crosses the intersection before the AV or stops for the AV to cross first. To calculate this measure, the timestamp at which the cyclist reaches the intersection point and the timestamp at which the AV reaches the intersection point are needed. If the cyclist reaches it before the AV, the value is equal to 1, and if the AV reaches it before the cyclist, the value is equal to 0. In cases where the cyclist already passed the intersection point before the eHMI is displayed, a "NaN" value is assigned, since the participant did not have the opportunity to perceive and respond to the interface.

The crossing intention can be used to evaluate the clarity of the eHMI and the trust in the AV. If, for example, the AV signals the cyclist to stop, but the cyclist still proceeds to cross, it indicates that the eHMI's message and the intention of the AV may not have been understood. Conversely, if the AV signals the cyclist to cross, but the cyclist decides to stop, it means the cyclist mistrusts the AV's intentions.

3.5.6 Post-experiment questionnaire

After the VR experiment is conducted, the participants are asked to fill in a post-experiment questionnaire to learn about their experiences and perceptions. The questionnaire focuses on several key aspects related to the participants' interaction with the AV and the different eHMIs, as well as their impression of the VR environment itself. The complete contents of the questionnaire are presented in Appendix A. It consists of 5 segments: 1) Questions on the participants' demographics. 2) Questions on the realism of the VR experiment. 3) The Simulator Sickness Questionnaire (SSQ). 4) The Presence Questionnaire (PQ). 5) Questions assessing the subjective measures of cyclists' crossing behaviour.

The first segment contains questions related to the participants' demographics, which consists of the characteristics age, gender, experience with VR, familiarity with the concept of AVs, familiarity with the concept of eHMIs, and frequency of cycling. The questions on experience with VR can be scored from "No experience" to "Expert", with a 5-point Likert scale. The scores for familiarity with AVs and eHMIs can range from "Not at all familiar" to "Very familiar", again using a 5-point Likert scale. Lastly, the frequency of riding a bicycle can be measured from "Less than once a day" to "Every day", with a 4-point Likert scale. Understanding the demographics of the participants is valuable for identifying potential patterns or biases in their responses and behaviour. For example, the familiarity with AVs and eHMIs may shape how participants interpret the visual cues of the AV, which can influence their crossing decisions. Including information on the demographics therefore provides context for interpreting the results.

The next part of the questionnaire is dedicated to feedback on the overall realism of the VR experience and virtual environment. It contains questions assessing the realism of visuals, behaviour of the AV, movement of the bicycle and background audio. Scores can be given on a 5-point Likert scale ranging from "Not at all" to "Extremely". These questions are important as the realism of the virtual environment can influence the engagement of the participants. When the virtual environment is immersive and convincing, it is more likely to stimulate natural behaviour and therefore increases the validity of the experiment.

The SSQ assesses the participants' level of simulation sickness symptoms, such as nausea, dizziness and general discomfort, after performing the VR experiment (Kennedy et al., 1993). For each symptom the participant can indicate how much it is affecting them, by selecting either "None", "Slight", "Moderate" or "Severe". The SSQ is a widely used tool in VR experiments and is highly appreciated in VR research. It is useful to monitor the well-being of the participants during the VR experiment and is used to validate and evaluate the VR setup of the experiment.

The PQ assesses the level of immersion of the experiment and the degree to which the participants felt present in the virtual environment (Witmer and Singer, 1994). It covers several factors, such as the level of immersion, involvement, interface quality and sensory fidelity. The PQ is standardized tool used widely in VR research to evaluate how effectively a virtual environment engages users and creates a sense of presence. This is important as it can influence how participants perceive and respond to the virtual world.

The final segment of the questionnaire consists of questions related to the subjective measures that capture key aspects of cyclists' crossing behaviour. The participants are asked to evaluate the following six measures for each of the four eHMI designs: perceived risk, perceived safety, trust in AV, clarity of eHMI, decision-making and preferences regarding eHMI design. For each measure and eHMI type, the participant has to give a score on a 5-point Likert scale. The results are essential for understanding how cyclist interpret and respond to the different eHMIs. By comparing these subjective measures across all eHMI types it provides valuable insight into which designs are most effective in enhancing communication between cyclist and AV.

4 Results

In this chapter, the findings from the data analysis of the experiment are presented, including both the experimental data and the responses to the post-experiment questionnaire. The first subsection explains the results of the objective measures of cyclists' crossing behaviour, gathered from the data of the VR experiment itself. It includes findings on the measures explained in Section 3.5. The second subsection includes the findings of the subjective measures of cyclists' crossing behaviour, which are extracted from the post-experiment questionnaire. The final subsection presents the results related to the user experience in the VR experiment, including participants' responds to the questions about the perceived realism of the experiment, the Simulator Sickness Questionnaire (SSQ) and the Presence Questionnaire (PQ).

4.1 Analysis of cyclists' behaviour from VR experiment

In this section, the data collected during the VR experiment are presented and analyzed. It consists of the following objective measures: crossing initiation time, crossing time, speed change, gazing time and crossing intention. For each measure, the findings are analyzed and compared across the different eHMI designs to be able to assess how each design affects the crossing behaviour of the cyclists.

To determine whether the impact of the eHMI designs are significant, statistical modeling techniques are applied. For continuous variables, such as the crossing initiation time, crossing time, speed change and gazing time, Linear Mixed Models (LMM) are used to analyze the outcomes. This model allows for both fixed effects and random effects, which can be useful when repeated measurements are made during the data collection. In this case, since each participant has performed the same scenarios for multiple eHMIs, there are repeated measurements in the data. The random effects, therefore, capture the individual differences between the participants. The fixed effects of the LMM account for the different eHMI types, which consist of No eHMI, Textual eHMI, Symbolic eHMI and Light eHMI, and the yielding condition of the AV (yielding or not yielding). The baseline condition of the model consists of "no eHMI" and "yielding", meaning that all other conditions are compared against this reference point. The general equation for a LMM is in the form (UCLA Statistical Consulting Group, n.d.):

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\boldsymbol{u} + \boldsymbol{\varepsilon} \tag{2}$$

In this equation, $\mathbf{Y}$ is the dependent variable, representing one of the measured outcome variables (e.g. crossing initiation time, crossing time, speed change, gazing time). The independent variable $\mathbf{X}$ represents the matrix of the predictor variables, which consists of the type of eHMI (e.g. no eHMI, textual, symbolic, lights) and the yielding condition (e.g. yielding, not yielding). $\boldsymbol{\beta}$ represents the fixed effects coefficients associated with these predictors. Then $\mathbf{Z}$ is the design matrix for the random effects and $\boldsymbol{u}$ is a vector of the random effects coefficients, capturing the variability between participants. Finally, $\boldsymbol{\varepsilon}$ represents the vector of residual errors.

For the crossing intention, which is a binary measure, a Generalized Linear Mixed Model (GLMM) is used, which is an extension of the LMM. This model captures both fixed effects and random effects, while also accommodating binary outcomes, which a LMM is not able to do. In the same manner, the random effects account for the individual differences between the participants, and the fixed effects account for the different eHMI types and the yielding condition. The general equation for a GLMM is in the same form as the equation of the LMM, indicated in Equation 2. The dependent variable $\mathbf{Y}$, in this case, represents the crossing intention, and the independent variable $\mathbf{X}$ represents the type of eHMI and the yielding condition.

In a LMM, categorical independent variables are typically coded with a baseline condition. In this analysis, the "no eHMI" condition serves as the baseline eHMI type for the model. It then compares the effect of the other eHMI types with the baseline, estimating how each eHMI type influences the target variable compared to the "no eHMI" condition. However, this does not allow for direct comparisons between the other non-baseline conditions. To enable such comparisons between the other three eHMI types (textual, symbolic, lights), additional analysis is necessary. For this purpose, post-hoc pairwise comparisons are performed. These post-hoc tests apply the Tukey adjustment, which adjusts the confidence interval for each pairwise comparison to help maintain the reliability of the results (Minitab, n.d.).

4.1.1 Crossing initiation time

The first measure that has been analyzed is the crossing initiation time. In Figure 16, the box plots of the distribution of the crossing initiation time across the four different eHMI types are displayed. Both the results for the scenarios in which the AV yields the cyclist and the scenarios in which the AV does not yield the cyclist are presented in the figure. In both conditions, the crossing initiation time for the "no eHMI" type shows the highest median (median when yielding = 0.755, median when not yielding = 0.816), with large interquartile ranges. For the "yielding" condition, the medians of the textual (median = 0.433) and light eHMI (median = 0.400) are the lowest, indicating a quicker response, with relatively small interquartile ranges. For the "not yielding" condition, the median of the textual eHMI also displays the lowest value (median = 0.383), therefore indicating quick responses in both condition. Last of all, in the "yielding" condition, the spread of the symbolic eHMI is relatively large, indicating more variation in how the participants react to this interface.

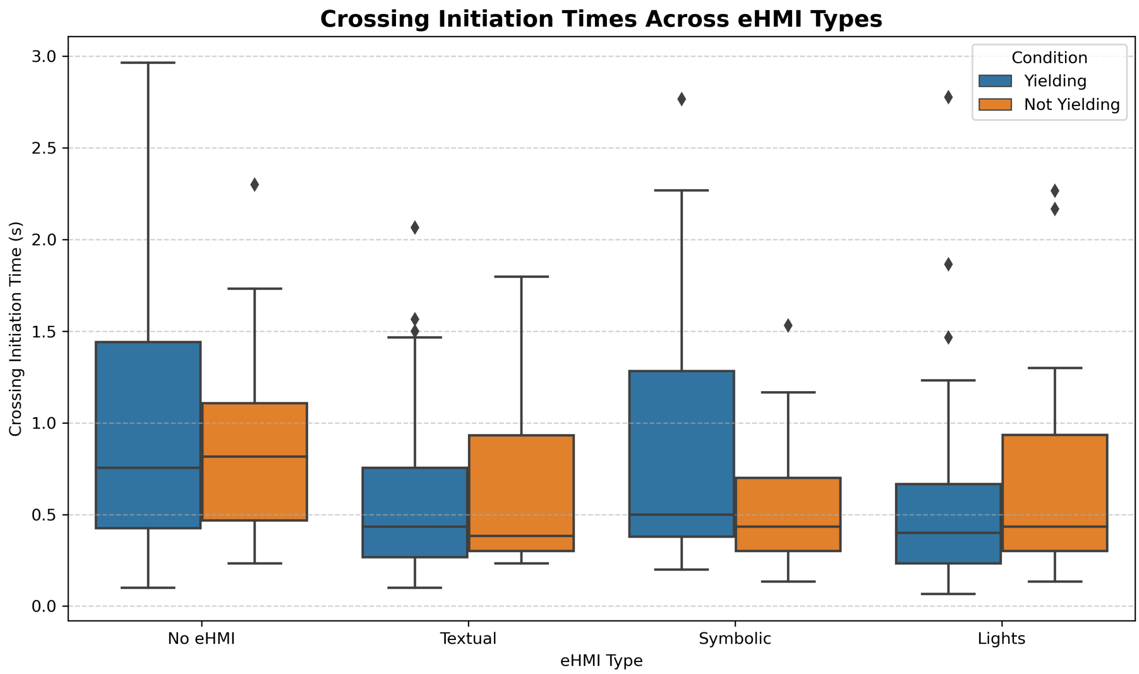


Figure 16: Box plots of the crossing initiation times

To understand whether these differences among the different eHMI types are statistically significant, a Linear Mixed Model (LMM) is used, as explained in the previous section. The results of this model, including both fixed and random effects, are shown in Table 5. It presents the estimated coefficients for each predictor, their standard errors, z-values, 95% confidence intervals and p-values to assess statistical significance. Statistical significance is typically determined using a threshold of $p < 0.05$, meaning that effects with p-values below this threshold indicate that the difference from the baseline is considered to be statistically significant. Therefore, the observed effect is unlikely due to random variation.

The results of the fixed effects suggest that most of the conditions do not show any statistical differences in crossing initiation time compared to the baseline. However, both the textual eHMI ($p = 0.002$) and lights eHMI ($p = 0.003$) showed significantly lower initiation times compared to "no eHMI". For the symbolic eHMI, no significant difference is observed ($p = 0.203$). For the "not yielding" condition, none of the effects reached statistical significance, indicating that the eHMI type did not significantly influence the crossing initiation time when the AV was not yielding.

Since both the textual and light eHMI display a significant difference compared to the baseline condition of "no eHMI", a post-hoc pairwise comparison is made to determine whether there are significant differences between these specific eHMI types. The results of the post-hoc tests for the "yielding" condition are presented in Table 19 of Appendix B, and the results for the "not yielding" condition are presented in Table 20. As shown, in both conditions there are no significant differences observed between the textual and light eHMI. This suggests, that both eHMI types significantly decrease the crossing initiation time compared to the "no eHMI" type, however their effects are statistically comparable. In other words, while both eHMI types are effective in decreasing the crossing initiation time, there is no statistical evidence that one is more effective than the other. Furthermore, none of the other pairwise comparisons between the non-baseline eHMI types display any statistically significant effects.

When examining the results of the random effects, shown in Table 5 it can be observed that both the variance and standard deviation attributed to the participant ID are very small. The p-value ($p = 1.000$) indicates that there is no significant effect of the individual differences between participants on the crossing initiation time. It even indicates that the random effects do not contribute to any improvement in the model fit, which suggests that the random effects could potentially be omitted from the model.

Table 5: LMM results for crossing initiation time

Fixed Effects	**Coef.**	**SE**	**z**	**CI**	**p**
$\boldsymbol{\beta}_{\textbf{Intercept}}$	**1.069**	**0.111**	**9.648**	**[0.852, 1.286]**	**<0.001**
$\boldsymbol{\beta}_{\textbf{Textual}}$	**-0.447**	**0.146**	**-3.063**	**[-0.733, -0.161]**	**0.002**
β_{Symbolic}	-0.188	0.148	-1.274	[-0.478, 0.102]	0.203
$\boldsymbol{\beta}_{\textbf{Lights}}$	**-0.444**	**0.149**	**-2.974**	**[-0.736, -0.151]**	**0.003**
$\beta_{\text{NotYielding}}$	-0.219	0.144	-1.513	[-0.502, 0.065]	0.130
$\beta_{\text{Textual}\times\text{NotYielding}}$	0.279	0.208	1.345	[-0.128, 0.687]	0.179
$\beta_{\text{Symbolic}\times\text{NotYielding}}$	-0.102	0.206	-0.493	[-0.505, 0.302]	0.622
$\beta_{\text{Lights}\times\text{NotYielding}}$	0.270	0.207	1.307	[-0.135, 0.675]	0.191
Random Effects	**Var.**	**SD**	**p**		
Participant (ID)	0.056	0.050	1.000		

4.1.2 Crossing time

For the crossing time, the box plots for both "yielding" and "not yielding" are shown in Figure 17. The overall medians of the crossing time are all higher for "not yielding" compared to "yielding". This seems to be logical, as in the latter the cyclists do not have to stop for the AV, meaning they can cross more quickly. The spread of the crossing times is larger when the AV is yielding and has larger interquartile ranges. In case of yielding, the median and spread of the crossing time is the largest for the symbolic eHMI (median = 5.009), and the median is the lowest for the textual eHMI (median = 3.962). When the AV is not yielding, the median is the largest for the light eHMI (median = 7.608) and the lowest for the "no eHMI" (median = 6.201).

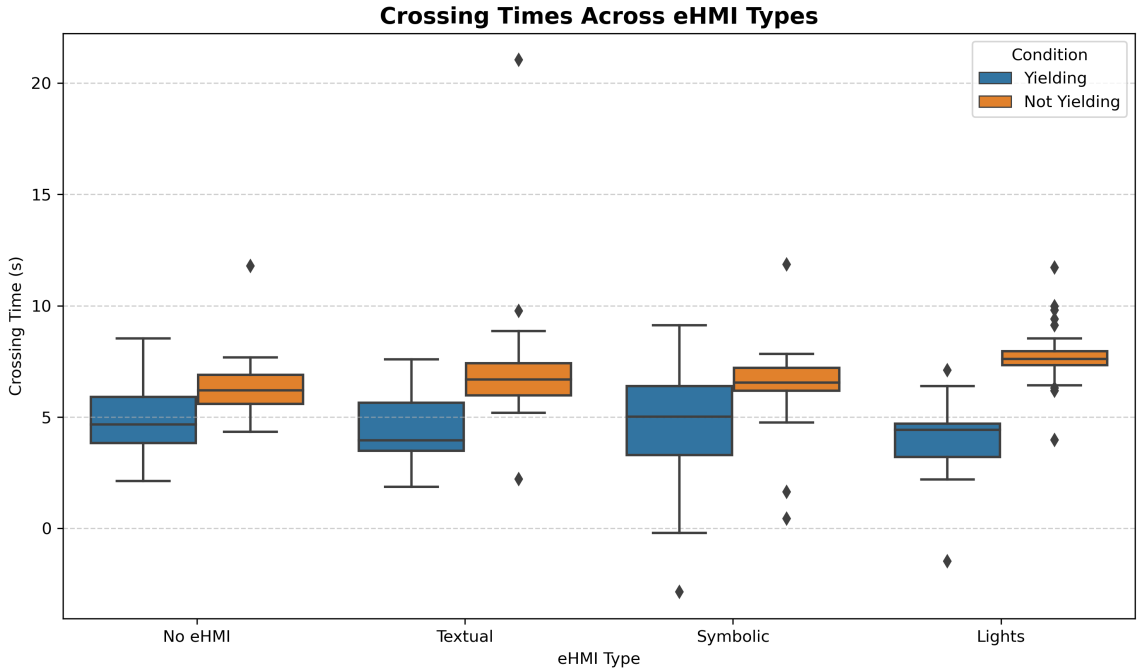


Figure 17: Box plots of the crossing time

The results for the fixed and random effects of the LMM are displayed in Table 6. In case of the AV is yielding, there seems to be no significant difference between any of the eHMI types. When comparing the crossing time for the "not yielding" condition to the baseline, it shows a p-value of 0.001. This indicates that the crossing time is significantly higher when the AV is not yielding to the cyclist. As explained before, this seems to be logical, as the vehicle does not stop for the cyclist, having them wait longer. Furthermore, there is a significant effect of the light eHMI on the crossing time when the AV is not yielding ($p = 0.002$). The crossing time increases in this case by 2.145 seconds compared to the baseline.

The LMM results for the random effects of the crossing time show a p-value of <0.001, which indicate a highly statistical significant effect of the random intercept on the model fit. This means that the individual differences between participants significantly influence the crossing times.

Table 6: LMM results for crossing time

Fixed Effects	**Coef.**	**SE**	**z**	**CI**	**p**
$\boldsymbol{\beta}_{\textbf{Intercept}}$	**4.799**	**0.371**	**12.923**	**[4.071, 5.527]**	**<0.001**
β_{Textual}	-0.394	0.485	-0.812	[-1.345, 0.557]	0.417
β_{Symbolic}	-0.100	0.491	-0.203	[-1.063, 0.864]	0.839
β_{Lights}	-0.758	0.496	-1.529	[-1.730, 0.214]	0.126
$\boldsymbol{\beta}_{\textbf{NotYielding}}$	**1.526**	**0.480**	**3.178**	**[0.585, 2.468]**	**0.001**
$\beta_{\text{Textual}\times\text{NotYielding}}$	1.193	0.691	1.727	[-0.161, 2.547]	0.084
$\beta_{\text{Symbolic}\times\text{NotYielding}}$	0.197	0.685	0.288	[-1.145, 1.539]	0.773
$\boldsymbol{\beta}_{\textbf{Lights}\times\textbf{NotYielding}}$	**2.145**	**0.687**	**3.122**	**[0.798, 3.492]**	**0.002**
Random Effects	**Var.**	**SD**	**p**		
Participant (ID)	0.685	0.174	<0.001		

4.1.3 Speed change

As explained in Section 3.5, the speed change is determined by calculating the maximum acceleration rate after the eHMI is shown. The results across the different eHMIs are highlighted in Figure 18, which shows the box plots for the "yielding" condition and the box plots for the "not yielding" condition. The differences in both the median values and the spread of the values seem to be relatively small in case of the "yielding" condition. In this case, the median and interquartile ranges are the largest for the "no eHMI" (median = 13.027), and the median is the lowest for the textual eHMI (median = 11.575). For the "not yielding" condition, the acceleration rates seem to be more dispersed, especially for the symbolic and light eHMI, which show the largest spread. The median for the symbolic (median = 17.421) and light eHMI (median = 16.774) are also the highest, while the lowest median is observed for the textual eHMI (12.961).

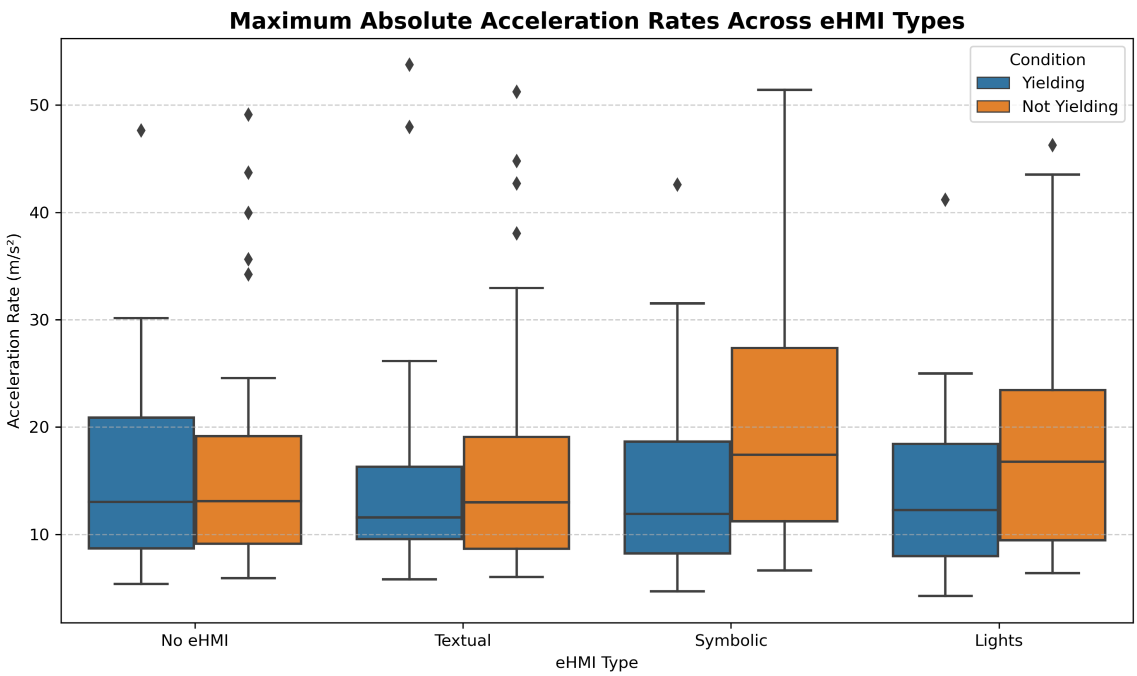


Figure 18: Box plots of the maximum acceleration rates

To assess whether the observed differences among the eHMI types are statistically significant, again a LMM is used. The results for the fixed effects are shown in Table 7. As shown, none of the fixed effects reached statistical significance. Although the interaction between the symbolic eHMI and the "not yielding" condition suggests a possible trend ($p = 0.080$), it does not meet the common threshold and is therefore not considered to be statistically significant. These findings suggest that, while there may be descriptive trends that hint at variations in the acceleration rates between some conditions, the observed effects are not strong enough to be considered statistically significant within this data set.

The results of the LMM for the random effects are also shown in Table 7. The variance is estimated at 21.14 with a p-value <0.001, indicating a high significance level. Therefore, it can be concluded that the random effects significantly improve the model fit, and therefore suggest that the participants show clear individual variation in maximum acceleration rates.

Table 7: LMM results for maximum acceleration rates

Fixed Effects	**Coef.**	**SE**	**z**	**CI**	**p**
$\boldsymbol{\beta}_{\textbf{Intercept}}$	**15.745**	**1.925**	**8.181**	**[11.973, 19.518]**	**<0.001**
β_{Textual}	-0.593	2.459	-0.241	[-5.412, 4.226]	0.809
β_{Symbolic}	-1.426	2.459	-0.580	[-6.245, 3.393]	0.562
β_{Lights}	-1.386	2.459	-0.564	[-6.204, 3.433]	0.573
$\beta_{\text{NotYielding}}$	1.197	2.459	0.487	[-3.621, 6.016]	0.626
$\beta_{\text{Textual}\times\text{NotYielding}}$	0.897	3.477	0.258	[-5.917, 7.712]	0.796
$\beta_{\text{Symbolic}\times\text{NotYielding}}$	6.095	3.477	1.753	[-0.719, 12.910]	0.080
$\beta_{\text{Lights}\times\text{NotYielding}}$	2.599	3.477	0.747	[-4.216, 9.413]	0.455
Random Effects	**Var.**	**SD**	**p**		
Participant (ID)	21.140	0.937	<0.001		

4.1.4 Gazing time

In Figure 19, the box plots of the cumulative yaw changes, calculated as explained in Section 3.5, are presented. The median values and spread of the yaw changes are relatively larger in case of the "not yielding" condition compared to the "yielding" condition. This could be due to the cyclist having to stop and wait for the AV to pass. The cyclist then has more time to look around and gaze towards the AV, which could account for the higher cumulative yaw changes. For the "yielding" condition, the highest median is observed for the "no eHMI" (median = 102.866), while the lowest median is observed for the symbolic eHMI (median = 75.744). In this condition, the spread of the values for all eHMI types is relatively low. For the "not yielding" condition, the highest median is observed for the light eHMI (median = 240.822) and the lowest median for the symbolic eHMI (89.493). Overall, the spread of the values is considerably larger in case the AV is not yielding.

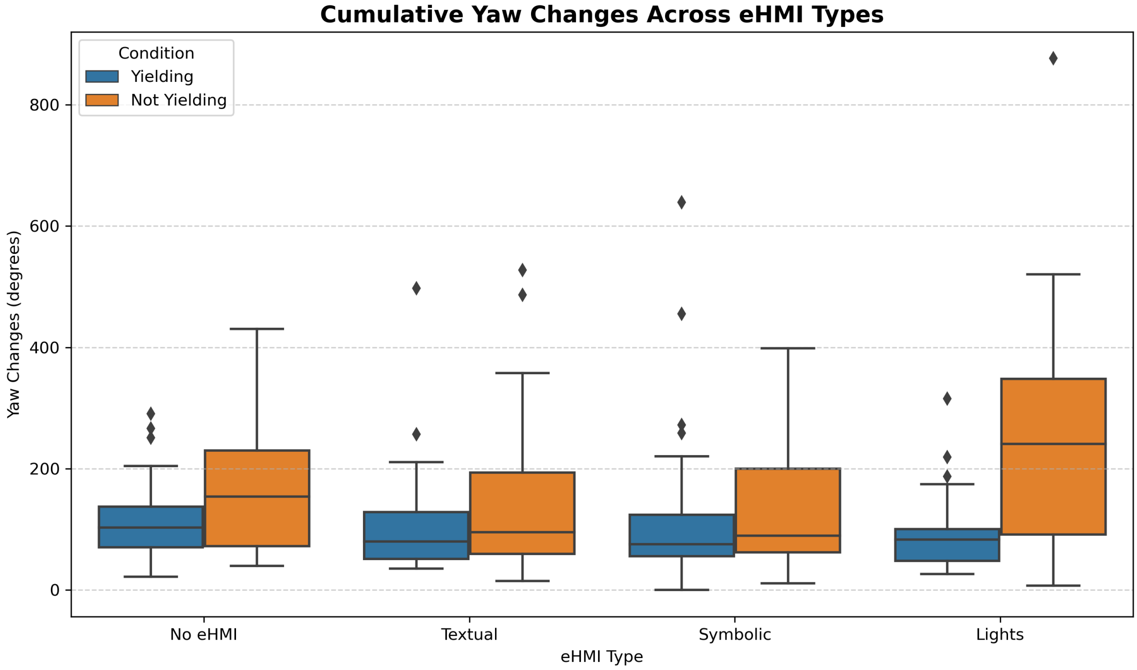


Figure 19: Box plots of the cumulative yaw changes

When examining the LMM results for the fixed effects, highlighted in Table 8, it can be observed that none of the eHMI types show statistically significant effects on the yaw changes in the "yielding" condition. However, the cumulative yaw changes significantly increase for the "not yielding" condition compared to the baseline ($p = 0.013$). Furthermore, the interaction effect between the light eHMI and the "not yielding" condition is significant. This indicates that the yaw changes, and thus the gazing time, are significantly higher when participants encountered the light eHMI when the AV was not yielding compared to the baseline. The comparisons between no eHMI, textual and symbolic eHMIs suggest no substantial or significant differences among the conditions.

Additionally, table 8 indicates the LMM results for the random effects of the cumulative yaw changes. It can be observed that the variance and standard deviation are considerably large. The p-values is highly significant ($p < 0.001$), indicating that the individual differences among the participants significantly contribute to the variability in cumulative yaw changes.

Table 8: LMM results for cumulative yaw changes

Fixed Effects	**Coef.**	**SE**	**z**	**CI**	**p**
$\boldsymbol{\beta}_{\textbf{Intercept}}$	**116.939**	**21.285**	**5.494**	**[75.222, 158.656]**	**<0.001**
β_{Textual}	-9.774	23.364	-0.418	[-55.566, 36.019]	0.676
β_{Symbolic}	6.413	23.364	0.274	[-39.379, 52.206]	0.784
β_{Lights}	-23.499	23.364	-1.006	[-69.292, 22.293]	0.315
$\boldsymbol{\beta}_{\textbf{NotYielding}}$	**57.994**	**23.364**	**2.482**	**[12.201, 103.786]**	**0.013**
$\beta_{\text{Textual}\times\text{NotYielding}}$	-13.530	33.042	-0.409	[-78.291, 51.230]	0.682
$\beta_{\text{Symbolic}\times\text{NotYielding}}$	-44.321	33.042	-1.341	[-109.081, 20.440]	0.180
$\boldsymbol{\beta}_{\textbf{Lights}\times\textbf{NotYielding}}$	**95.805**	**33.042**	**2.900**	**[31.045, 160.566]**	**0.004**
Random Effects	**Var.**	**SD**	**p**		
Participant (ID)	5583.137	19.927	<0.001		

4.1.5 Crossing intention

The last measure extracted from the experimental data is the crossing intention, which is a binary variable: a value of 1 indicates a participant crossing before the AV, while a value of 0 indicates crossing after the AV. Figure 20 shows the distribution of the crossing intentions across the different eHMI types, for both conditions, using stacked bar plots. In case of "yielding", the cyclists were supposed to cross before the AV, as the AV stops and yields to the cyclist. In this context, intended behaviour is represented by participants crossing before the AV, and is indicated in grey. The times that participants crossed after the AV are depicted in blue. A larger blue segment of the bar indicates a higher number of participants that did not behave as expected and misinterpreted the eHMI. In case of the "not yielding" condition, the participants were expected to wait and cross after the AV. As such, the intended response is crossing after the AV, and is again indicated in grey. Participants that crossed before the AV are depicted in red. Similarly, a larger red segment of the bar indicates a higher number of times the participants did not act as expected, and thus misinterpreted the eHMI. Therefore, in both subplots, a larger grey segment indicates better understanding and interpretation of the eHMI, reflecting higher clarity in communication.

As shown in the figure, for the "yielding" condition, the participants decided to cross before the AV the most amount of times when interacting with the light eHMI (participants who crossed after the AV = 30). During the scenarios where the symbolic eHMI was displayed, there were two instances in which the participants had already crossed before the eHMI was shown, resulting in a "NaN" value. Also, in this case, the most amount of times were recorded where the participants crossed after the AV (participants who crossed after the AV = 5). This indicates that the participants were more cautious when interacting with the symbolic eHMI. For the "not yielding" condition, the differences between the eHMI types are less noticeable. When interacting with the symbolic eHMI, the number of participants that crossed before the AV was the highest (participants who crossed before the AV = 4) compared to the other eHMI types, however the differences were minimal.

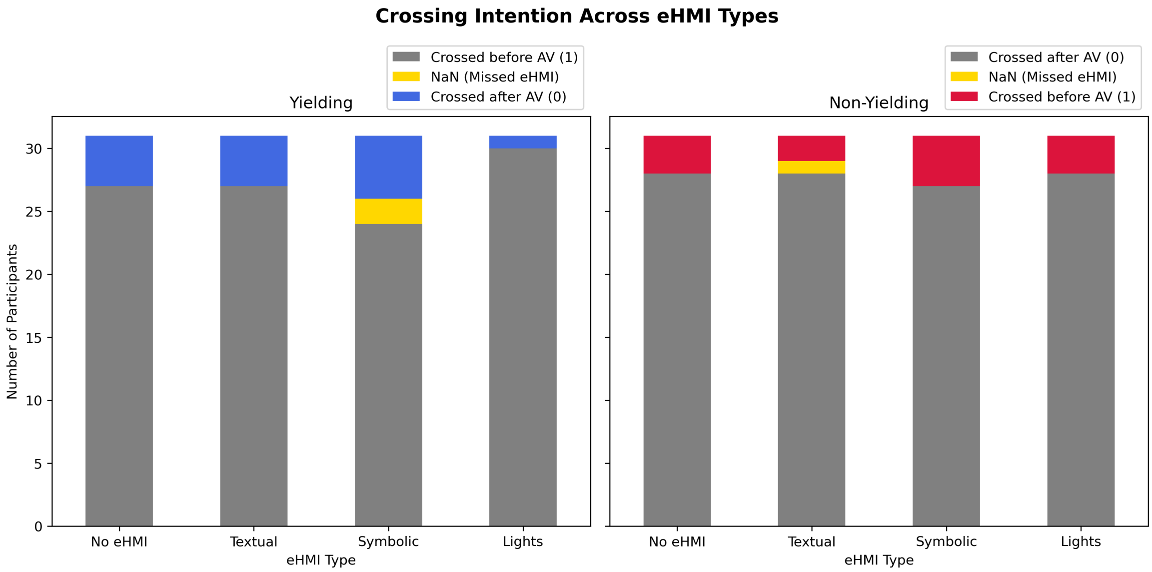


Figure 20: Bar plots of the crossing intentions

Since the outcomes of the crossing intentions are binary, a GLMM is used to analyze the results. Table 9 presents the results for both fixed and random effects of the GLMM. Among the fixed effects, no statistically significant difference is observed for any of the eHMIs types compared to the baseline condition (no eHMI and yielding). The textual eHMI showed a coefficient close to 0 with a p-value of 1.000, indicating no difference at all. The observed effect for the "not yielding" condition is statistically significant, indicating that participants were significantly less likely to cross in case of not yielding.

The results for the random effects of the GLMM highlights a variance of 1.703 and a standard deviation of 1.305, with a p-value of <0.001. This indicates that the random effects is statistically significant, and therefore the individual differences of the participants have a significant effect on the crossing intentions.

Table 9: GLMM results for crossing intentions

Fixed Effects	**Coef.**	**SE**	**z**	**CI**	**p**
$\boldsymbol{\beta}_{\textbf{Intercept}}$	**2.449**	**0.680**	**3.602**	**[1.116, 3.781]**	**<0.001**
β_{Textual}	0.000	0.832	0.001	[-1.629, 1.630]	1.000
β_{Symbolic}	-0.383	0.804	-0.477	[-1.959, 1.192]	0.634
β_{Lights}	1.735	1.244	1.395	[-0.703, 4.173]	0.163
$\boldsymbol{\beta}_{\textbf{NotYielding}}$	**-5.261**	**1.017**	**-5.171**	**[-7.255, -3.267]**	**<0.001**
$\beta_{\text{Textual}\times\text{NotYielding}}$	-0.418	1.305	-0.320	[-2.976, 2.140]	0.749
$\beta_{\text{Symbolic}\times\text{NotYielding}}$	0.753	1.182	0.638	[-1.563, 3.070]	0.524
$\beta_{\text{Lights}\times\text{NotYielding}}$	-1.735	1.543	-1.125	[-4.759, 1.289]	0.261
Random Effects	**Var.**	**SD**	**p**		
Participant (ID)	1.703	1.305	<0.001		

4.2 Analysis of cyclists' behaviour from questionnaire

This section presents the results obtained in the post-experiment questionnaire, which captures the subjective measures such as risk, safety, trust, decision-making, clarity and preferences of each eHMI type. Since responses are given on a Likert-scale, the outcomes are ordinal in nature. To analyze ordinal response data with participant-level random effects, a Cumulative Link Mixed Model is used, which is a type of mixed-effects ordinal logistic regression. This model incorporates both fixed and random effects, which similar to the models used for the experimental data allows for individual differences among participants. For example, one participant might experience more risk in general and therefore scores every question related to risk higher as a result. These random effects of repeated measures are taken into account in a CLMM. The fixed effects of the model account for the four different eHMI types. The CLMM uses the same general equation as the LMM, provided in Section 4.1:

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{Z}\boldsymbol{u} + \boldsymbol{\varepsilon} \tag{3}$$

$\mathbf{Y}$ represents the response variable, which indicates one of the target variables that is needed (e.g. perceived risk, perceived safety, trust in AV, clarity of eHMIs, decision-making, preferences). $\mathbf{X}$ is the design matrix for the fixed effects, which represents the different types of eHMIs (no eHMI, textual, symbolic, lights) and $\boldsymbol{\beta}$ is the vector of fixed effects coefficients. Then, $\mathbf{Z}$ is the design matrix for the random effects and $\boldsymbol{u}$ is the vector of random effects coefficients. Finally, $\boldsymbol{\varepsilon}$ is the vector of residuals.

Similarly to a LMM, explained in Section 4.1, a CLMM does not allow for direct comparisons between the non-baseline eHMI conditions. Therefore, post-hoc pairwise comparisons are performed using the Tukey-adjustment to enable these comparisons and determine whether statistically significant effects are observed between the non-baseline conditions.

4.2.1 Perceived risk

The CLMM results for the fixed effects of the questions related to the perceived risk are presented in Table 10. The model uses the "no eHMI" condition as baseline, for which the cross-comparisons with the other eHMIs all indicate a highly significant p-value. This means that having any eHMI results in a significantly lower perceived risk compared to using no eHMI. The coefficients indicate that the symbolic eHMI has the largest negative effect on the perceived risk (coef. = -3.222), followed by the textual eHMI (coef. = -3.059). By performing post-hoc pairwise comparisons, the three non-baseline eHMIs can be compared with one another. The results, shown in Table 21 of Appendix B, unveils that none of the cross-comparisons between the non-baseline eHMI types show any significant differences. Therefore it suggests that, while all three eHMI designs decrease the perceived risk compared to the baseline of "no eHMI", no significant differences between the textual, symbolic and light eHMI are observed.

Table 10 also displays the CLMM results for the random effects. As the p-value suggests, the random effect is highly significant ($p < 0.001$), meaning that the inclusion of it significantly improves the model fit. Therefore, the variability between participants in risk ratings are considerable and the results support the use of a mixed-effects approach.

Table 10: CLMM results for perceived risk

Fixed Effects	**Coef.**	**SE**	**z**	**p**
β_{Textual}	-3.059	0.599	-5.104	<0.001
β_{Symbolic}	-3.222	0.603	-5.341	<0.001
β_{Lights}	-2.182	0.552	-3.954	<0.001
Random Effects	**Var.**	**SD**	**p**	
Participant (ID)	3.652	1.911	<0.001	

4.2.2 Perceived safety

In Table 11, the CLMM results for the fixed and random effects of the perceived safety are displayed. Using the "no eHMI" condition as baseline, the results show that all other eHMI types significantly increase the perceived safety among participants. In particular, the symbolic eHMI showed the highest positive effect (coef. = 2.9130). The textual eHMI had the second highest positive effect on the perceived safety ratings (coef. = 2.147), and lights had the lowest positive effect (coef. = 1.861). The results of the post-hoc pairwise comparisons are presented in Table 22 of Appendix B. While all eHMI types showed a significant increase in perceived safety compared to the baseline of "no eHMI", no significant effect between any of the non-baseline eHMI conditions (textual, symbolic and lights) is observed. This implies that, although any eHMI improves the perceived safety compared to the absence of an eHMI, the differences were not statistically significant.

The results for the random effects of the CLMM, presented in 11 show statistical significance ($p < 0.001$). Therefore, the findings confirm that including individual-level variability improves the model fit and highlights that safety is perceived differently among participants.

Table 11: CLMM results for perceived safety

Fixed Effects	**Coef.**	**SE**	**z**	**p**
β_{Textual}	2.147	0.524	4.101	<0.001
β_{Symbolic}	2.913	0.557	5.232	<0.001
β_{Lights}	1.861	0.525	3.546	<0.001
Random Effects	**Var.**	**SD**	**p**	
Participant (ID)	1.628	1.276	<0.001	

4.2.3 Trust in AV

The CLMM results for the trust in AV, shown in Table 12, demonstrate a strong significance for all other eHMI types compared to a baseline condition of "no eHMI". Therefore, the use of any eHMI leads to significant more trust in the AV compared to using no interface. Among the eHMIs, the symbolic had the largest effect on the trust, with a coefficient of 3.291, followed by the textual eHMI (coef. = 2.938). The light eHMI had the lowest positive effect on the trust in the AV (coef. = 2.441). The results of the post-hoc pairwise comparisons are presented in 23 of Appendix B, and indicate that there are no statistically significant differences between the textual, symbolic and light eHMIs in terms of trust ratings.

Furthermore, the random effects of the CLMM, shown in 12 indicate substantial variability across participants. The p-value shows statistical significance ($p < 0.001$), hence suggesting that individual differences among participants have a significant influence on the trust ratings.

Table 12: CLMM results for trust in AV

Fixed Effects	**Coef.**	**SE**	**z**	**p**
β_{Textual}	2.938	0.569	5.168	<0.001
β_{Symbolic}	3.291	0.580	5.676	<0.001
β_{Lights}	2.441	0.553	4.419	<0.001
Random Effects	**Var.**	**SD**	**p**	
Participant (ID)	1.385	1.177	<0.001	

4.2.4 Clarity of eHMI

Table 13 presents the CLMM results for the fixed and random effects of the clarity of the eHMIs. The p-values show high significance levels for all other eHMI types compared to the baseline condition of "no eHMI". All three designs were found to have significantly higher clarity ratings, in particular the symbolic design, which showed the highest positive effect (coef. = 5.471). To know whether the non-baseline eHMI types display any statistical significant differences between one another, post-hoc pairwise comparisons are made, for which the results are shown in 24 of Appendix B. The findings show that between symbolic and lights a significant p-value was measured ($p = 0.028$). The positive estimate, therefore, indicates that the symbolic eHMI had significantly increased clarity ratings compared to the light eHMI. The cross-comparisons between textual and symbolic ($p = 0.356$) and between textual and lights ($p = 0.592$) did not show any significant differences.

The CLMM also incorporated random effects to account for participant-level variability, for which the results are shown in 13. As can be ssen, a significant p-value was measured ($p < 0.001$). Therefore, the individual differences among the participants have a significant impact on how clarity was rated across the eHMI types.

Table 13: CLMM results for clarity of eHMIs

Fixed Effects	**Coef.**	**SE**	**z**	**p**
β_{Textual}	4.671	0.715	6.538	<0.001
β_{Symbolic}	5.471	0.769	7.116	<0.001
β_{Lights}	4.069	0.681	5.977	<0.001
Random Effects	**Var.**	**SD**	**p**	
Participant (ID)	1.927	1.388	<0.001	

4.2.5 Decision-making

In Table 14, the CLMM results are presented for the decision-making of the participants. Compared to the baseline condition of "no eHMI", all other eHMI types demonstrated a highly significant positive effect. This implies that the participants found it considerably easier to make crossing decisions when any form of eHMI was present. The symbolic eHMI showed the highest positive effect to the decision-making of the participants (coef. = 4.107). Using post-hoc pairwise comparisons, it can be analyzed whether the three non-baseline eHMI types displayed any statistically significant differences. As can be seen, in Table 25 of Appendix B, the results show no significance difference for any of the comparisons between the textual, symbolic and light eHMIs.

In addition, the random effects of the model, shown in Table 14, reached statistical significance, and therefore significantly improved the model fit. It can be concluded that the individual differences between participants had a significant effect on how they scored their decision-making.

Table 14: CLMM results for decision-making

Fixed Effects	**Coef.**	**SE**	**z**	**p**
β_{Textual}	3.537	0.607	5.832	<0.001
β_{Symbolic}	4.107	0.635	6.465	<0.001
β_{Lights}	3.037	0.590	5.152	<0.001
Random Effects	**Var.**	**SD**	**p**	
Participant (ID)	1.892	1.376	<0.001	

4.2.6 Preferences regarding eHMI design

The last subjective measure to assess cyclists' crossing behaviour is the participant's preferences regarding eHMI design. The results of the CLMM are presented in Table 15, and show that all three eHMI types (textual, symbolic, lights) were significantly more preferred than no eHMI. This illustrates a strong overall preference towards AVs communicating their intentions via some form of interface, instead of indicating nothing at all. The coefficient for the symbolic eHMI is the highest (coef. = 4.7024), suggesting the strongest positive effect on the participants preferences. The post-hoc pairwise comparisons, for which the results are presented in Table 26 of Appendix B, indicate no significant difference between any of the non-baseline eHMI types (textual, symbolic and lights). Therefore, the findings suggest that any form of eHMI is preferred compared to not using an eHMI, however, the exact eHMI type to be preferred the most is inconclusive.

The results for the random effects of the CLMM are presented as well in Table 15. Interestingly, the random effect of the model was not significant ($p = 0.885$), indicating minimal individual variability among participants when rating their preferences. While this may imply that a fixed-effects model would suffice, the inclusion of the random effects ensures consistency with the overall modeling approach and accounts for potential individual differences, even if minimal.

Table 15: CLMM results for preferences regarding eHMI design

Fixed Effects	**Coef.**	**SE**	**z**	**p**
β_{Textual}	3.807	0.660	5.765	<0.001
β_{Symbolic}	4.702	0.694	6.776	<0.001
β_{Lights}	3.734	0.652	5.725	<0.001
Random Effects	**Var.**	**SD**	**p**	
Participant (ID)	0.042	0.204	0.885	

4.3 User experience in VR experiment

This section provides the results for the participants' overall user experience during the VR experiment, obtained in the post-experiment questionnaire. The user experience covers three aspects: the realism of the virtual environment, the level of simulation sickness measured by the SSQ, and the sense of presence during the experiment measured by the PQ. Together, these measures provide insight into how immersive, realistic, and comfortable the VR experience was for participants.

4.3.1 Realism of the VR experiment

The first aspect of the user experience consists of the questions related to the realism of the VR experiment. Ratings are given on a 5-point Likert scale for which Table 16 presents the mean and standard deviation per question. As can be seen, the questions regarding the visuals, the behaviour of the AV and the movement of the bicycle scored relatively high. This indicates that those aspects of the VR experiment were realistically depicted. The background audio scored the lowest on the questionnaire (M = 2.87, SD = 0.88), indicating that the audio did not feel as realistic as other aspects of the VR experiment. In this experiment, however, the audio was not an essential component for task performance. The audio used was a generic ambient sound, without any task-related cues. This could be the reason why the score is lower in the questionnaire. The overall ratings for the realism do indicate that the VR experiment was considered to be realistic.

Table 16: Mean and standard deviation of realism ratings (score 1 to 5)

Question	**Mean**	**SD**
How realistic did the visuals of the VR simulation feel?	3.48	0.77
How realistic did the behaviour of the automated vehicle?	3.61	0.80
How realistic did the movement of the bicycle feel?	3.65	0.66
How realistic did the background audio feel?	2.87	0.88

4.3.2 Simulator Sickness Questionnaire (SSQ)

The Simulator Sickness Questionnaire (SSQ) is conducted to establish to what extent the participants experienced any simulation sickness during the VR experiment. It contains a number of symptoms to which the participants can give a score using a 4-point Likert scale in order to assess how much each symptom is affecting them after the experiment is completed. The SSQ is divided into three sub-scales (nausea, oculomotor and disorientation) and a total score. The sub-scales are calculated by adding the scores for each symptom in the sub-scale and multiplying the total by a specified weight. The calculation is extracted from Kennedy et al., 1993. The mean and SD for each sub-scale are presented in Table 17. Oculomotor received the lowest score of the three sub-scales (mean = 16.14), suggesting a low level of visual and eye strain symptoms, while disorientation received the highest score (mean = 30.09), indicating a more prominent presence of symptoms such as dizziness and vertigo. The total score seems to suggest that the participants did experience noticeable simulator sickness, but it was not severe. Therefore, the overall experience was generally tolerable and falls within expected ranges.

Table 17: Mean and standard deviation of SSQ scales

Scale	**Mean**	**SD**
Nausea	23.08	21.44
Oculomotor	16.14	18.44
Disorientation	30.09	37.02
Total score	25.09	25.02

4.3.3 Presence Questionnaire (PQ)

To measure the extent to which the participants felt a sense of presence within the VR environment, the Presence Questionnaire (PQ) is conducted. The questions in the PQ are scored on a 3-point Likert scale and consists of four different sub-scales (Witmer and Singer, 1994): involvement, sensory fidelity, immersion and interface quality. The mean and SD of each sub-scale are presented in Table 18. The results indicate that the interface quality of the experiment scored the lowest (mean = 1.56), implying that participants may have experienced some limitations with the interface. The immersion sub-scale scored the highest (mean = 2.69), indicating that the participants felt well-integrated into the virtual environment. The highest standard deviation was measured for the sensory fidelity (SD = 0.48), indicating more variability in the scores. The mean for involvement (mean = 2.38), which is moderately high, suggests that participants were fairly engaged during the experiment. Overall, the results seem to demonstrate a moderately high level of presence during the VR experiment.

Table 18: Mean and standard deviation of PQ scales (score 1 to 3)

Scale	**Mean**	**Std. Dev.**
Involvement	2.38	0.36
Sensory Fidelity	2.02	0.48
Immersion	2.69	0.30
Interface Quality	1.56	0.44

4.4 Overview of results

As this chapter has presented a wide range of results, the amount of information could be somewhat overwhelming. Therefore, the following section provides an overarching summary of the key results that connects both the objective and subjective findings.

For the objective measures, significant differences between eHMI designs were observed for the crossing initiation time. The textual and light eHMI significantly decreased the crossing initiation time compared to not using any eHMI. For the other objective measures, the comparisons between eHMIs did not seem to be statistically significant compared to the baseline. Furthermore, whether the AV was yielding or not significantly impacted the crossing time, gazing time and crossing intentions.

While the objective measures did not consistently support the idea that the use of eHMIs enhance the efficiency of cyclists' crossing behaviour, the subjective responses to the questionnaire indicated a stronger preference. Across all subjective measures, the presence of any eHMI significantly improved participants' ratings compared to using no eHMI. The differences between the individual eHMI designs, however, were minimal, as only the clarity ratings showed a statistically significant difference, between the symbolic and light eHMI, where the symbolic eHMI scored a higher rating. Notably, the symbolic eHMI did seem to consistently receive the highest ratings across all subjective measures, even though this trend was not necessarily reflected in the behavioural outcomes of the objective data. Therefore, this indicates a potential gap between how participants feel about certain eHMI designs and how these interfaces actually influence their behaviour.

5 Discussion

In this chapter, the discussion of the results is provided. First, a short recap of the problem definition and research gap is given, to re-establish the context and objectives of this study. Then, a summary and interpretation of the main findings from Chapter 4 is given, and the research questions posed in Chapter 1 are answered. Finally, the key limitations of the study are given and the chapter concludes with providing recommendations for further research.

5.1 Recap of problem definition and research gap

As the integration of autonomous vehicles (AVs) into urban transport systems increases, the need to study their interactions with vulnerable road users (VRUs), such as pedestrians and cyclists, becomes even more critical. Unlike conventional vehicles, AVs lack human drivers and therefore are not able to use natural, social forms of communication, such as eye contact and hand gestures. This could pose challenges in mixed-traffic environments, in particular in shared space areas. In these urban settings, due to the absence of traditional traffic signs and right-of-way rules, safe interactions between road users rely heavily on social cues and communication.

To solve this problem, external Human-Machine Interfaces (eHMIs) are proposed to function as communication tools in order to convey AV intentions towards other road users, in specific VRUs. Although substantial research has been conducted on the effect of eHMIs on pedestrian behaviour when interacting with an AV, only little attention has been directed towards cyclist-AV interactions. As cyclists have unique behavioural characteristics compared to pedestrians, such as different speeds, mobility and positioning, findings from pedestrian-AV focused studies cannot be directly applied. Therefore, it is essential to conduct research on the effect of eHMIs on cyclist-AV interactions.

Virtual Reality (VR) offers a promising method for systematically researching these interactions in a safe and controlled environment. VR experiments allow for the replication of realistic and immersive traffic scenarios and capture intricate behavioural data without exposing participants to actual risks or dangers. This makes it very suitable for studying cyclist-AV interactions.

The objective of this study is to assess the effect of different eHMIs on cyclists' crossing behaviour when interacting with AVs in a shared space environment. To achieve this, a VR experiment is conducted in which participants use a bicycle simulator to engage in a series of crossing scenarios involving an interaction with an AV that is equipped with different types of eHMIs. In addition, the participants are asked to evaluate their perceptions and experiences in a post-experiment questionnaire. This approach allows for the collection of both objective data, from the VR experiment, and subjective data, from the post-experiment questionnaire, providing a comprehensive understanding of cyclists' crossing behaviour.

5.2 Interpretation of the results

This section provides a detailed interpretation of the results presented in Chapter 4. It is divided into three subsections: the first discusses the objective measures derived from the experimental data; the second focuses on the subjective measures obtained from the post-experiment questionnaire; and the third revisits the main and sub-questions of the research and provides answers based on the study's findings.

5.2.1 Objective measures from VR experiment

The VR experiment investigated the effect of four different eHMIs: no eHMI, textual, symbolic, and lights. Participants encountered scenarios where the AV either yielded to the cyclist or did not yield to the cyclist, under each eHMI condition. The objective measures that were extracted from the experimental data to understand the crossing behaviour of cyclists are: crossing initiation time, crossing time, speed change, gazing time, and crossing intention.

The findings revealed that both the textual eHMI and light eHMI significantly decreased the crossing initiation time of the participants compared to the baseline condition of "no eHMI". This indicates that both forms of eHMIs may assist cyclists in making quicker and more efficient decisions, because they are clear and easily interpreted. No significant reduction in the initiation time was measured for the symbolic eHMI, which suggests it may be less intuitive or more difficult to interpret. Interestingly, the initiation time was not affected by whether the AV was yielding or not.

For the crossing time, no significant differences were measured when comparing the other eHMI types with the baseline condition of "no eHMI". However, the "yielding" condition, had a significant effect, increasing the crossing time of the participants compared to when the AV did not yield. This suggests that cyclists take longer to cross when the AV does not yield, which is logically explained by the need of the cyclist to stop and wait for the AV to cross. Furthermore, the interaction effect between the light eHMI and the "not yielding" condition was found to be significant. A positive coefficient means that these conditions significantly increase the crossing time of participants compared to the baseline condition. While this increase in mainly attributed to the AV not yielding, since the cyclist has to wait for the AV to pass, the presence of the light eHMI shows a greater impact than the other eHMIs. This suggests that the lights may introduce a potential hesitation or uncertainty by the participants when the AV is not yielding. Finally, the lack of significant differences between the eHMI types in the "yielding" condition indicates that, once the cyclist starts crossing, the type of eHMI has little effect on how long it takes them to complete this action.

The findings for the speed change did not show any significant effects. Regardless of the AV's behaviour or the presence of any communication cues, cyclists appeared to be keeping a relatively constant speed throughout the encounters. This implies that either cyclists do not seem to adjust their speed significantly in response to the AV's behaviour or presence of an eHMI, or the speed changes may be too subtle to be accurately recorded. For the latter, it could be due to the way the speed change was defined in 3.5, using a 3-second time window. This threshold is able to capture noticeable changes in speed, however, might not fully capture potential delayed reactions that happen after the specified time window. Additionally, cyclist could be gradually varying their speed around a steady pace, which means that, while there is a response, no significant deviation is measured.

When analyzing the gazing time of the participants, determined by the cumulative head yaw changes, no significant difference was measured for any of the eHMI comparisons with the baseline condition of "no eHMI". However, when the AV did not yield, the yaw changes significantly increased compared to when the AV did yield. This can be explained logically as the cyclist needs to stop and wait for the AV to cross, therefore having more time to gaze towards the AV. It also is a more critical situation than when the AV yields and thus requires better observations of the AV's movement to safely interact. Furthermore, the interaction between the light eHMI and "not yielding" condition showed a significant increase in gazing time compared to the baseline. The longer gazing times for the light eHMI indicate that the interface might be unclear or more difficult to interpret.

Finally, the type of eHMI did not have a significant effect on the crossing intentions of the participants. In case of the "not yielding" condition, however, the crossing intentions showed a significant decrease compared to the "yielding" condition. The reason for this, is that when the AV does not yield to the cyclist, the cyclist has to stop, therefore significantly decreasing the crossing intentions in these scenarios.

To support and validate the findings, they can be compared to existing literature. First of all, similar to the study by Feng, Farah, and Arem (2023), this study did not find significant differences in crossing intentions between eHMI and non-eHMI conditions. The same study found that gazing behaviour, however, was impacted by the presence of an eHMI, directing attention more effectively towards the AV. In this study, only a significant increase in gazing time was measured for the light-based eHMI during the "not yielding" condition, suggesting increased attention towards the AV, but potentially due to confusion or difficulty interpreting the signal rather than clarity. Overall, Kaß et al. (2020) found that the use of any eHMI led to more effective and efficient behaviour of cyclists. This claim is only partially supported by the findings in this study, as the presence of an eHMI does influence cyclist behaviour, but it does not consistently demonstrate improved efficiency across all objective measures. Finally, Bazilinskyy, Dodou, and De Winter (2019) found that textual messages were generally clearer and more persuasive than non-textual eHMIs. This is partially in line with the findings from the experimental data in this study, as they do seem to increase the crossing initiation time of cyclists. However, no significant improvements were found in any of the other behavioural measures.

Overall, the results of the experimental data show that the use of any eHMI does have an effect on cyclist crossing behaviour, however their impact seems to be inconsistent. While using a textual or light display can assist in quicker decision-making when the AV is yielding, the use of an eHMI does not influence any of the other behavioural metrics. A symbolic-based interface was less effective, suggesting potential issues in understanding its message. In the "not yielding" condition, the light-based eHMI significantly increased the crossing time and gazing time of the cyclists, indicating that this interface is potentially more difficult to interpret. Lastly, the random effects of all measures (except crossing initiation time) showed a significant effect, which means that individual differences among participants significantly influence their crossing behaviour.

5.2.2 Subjective measures from questionnaire

In the post-experiment questionnaire, the participants were asked to rate their subjective perceptions and experiences from the VR experiment. For each eHMI design, they evaluated the following aspects: perceived risk, perceived safety, trust in AV, clarity of eHMI, decision-making, and preferences regarding eHMI design.

The findings showed that across all subjective measures, each eHMI type displayed a statistically significant improvement compared to the baseline condition of "no eHMI". This indicates that the presence of any eHMI leads to a more positive perception of cyclists' interaction with AVs. Among the different types of eHMIs, the symbolic consistently showed the largest effect on each measure, followed by the textual eHMI, and lastly the light eHMI. This suggests that cyclists generally perceive symbolic eHMIs to be the most effective in terms of clarity, safety and intuitiveness. Textual eHMIs, while also effective, may require more effort to interpret, and light-based eHMIs seem to be the least preferred. Additionally, the random effects for each of the measures reached statistical significance, indicating that individual differences among cyclists have a significant effect on how eHMIs are perceived.

To determine whether the differences between the non-baseline eHMI types are significant, post-hoc pairwise comparisons have been made. These post-hoc tests showed that the symbolic eHMI scored a significantly higher clarity rating compared to the light eHMI. However, none of the other pairwise comparisons reached statistical significance for the remaining subjective measures. These results suggest that although all eHMI designs were rated significantly better than the absence of an eHMI, the overall differences in ratings between the three designs were relatively small.

To validate the findings, the results of this study are compared to existing literature. Faas, Mathis, and Baumann (2020) found that any form of eHMI leads to better trust in AVs and perceived safety. These findings are in line with the results of this study as all eHMI types significantly improved participants' trust in the AV and perceived safety compared to using "no eHMI". Furthermore, in a study by Bazilinskyy, Dodou, and De Winter (2019), textual messages were found to be clearer and more persuasive than non-textual eHMIs. This is only partially supported by the subjective findings from this study, as the clarity ratings of the textual eHMI were higher than those of the light-based eHMI, however, the symbolic eHMI received the highest clarity ratings. The differences were not found to be statistically significant, therefore the findings do not support the literature's claim that textual eHMIs are clearer than non-textual eHMIs.

When comparing these subjective results gathered from the post-experiment questionnaire with the objective behavioural data obtained during the VR experiment, some interesting patterns come up. While the objective data shows that the presence of any eHMI can influence cyclists' crossing behaviour, the effects were not consistent across all behavioural metrics. On the other hand, the subjective measures clearly indicate a strong and consistent preference for the presence of any eHMI over having none, with all designs rating significantly higher than the baseline. When determining which eHMI type is perceived as the most efficient or helpful to cyclists, the results remain somewhat inconclusive. Whereas the experimental data suggests that symbolic eHMIs may be less clear or intuitive than for example textual displays, the subjective responses awarded the highest ratings for the symbolic eHMI in terms of clarity, trust and overall preferences. Therefore, a potential gap between perceived and actual usability is observed. Cyclists may feel more confident or positive towards a given design, however it does not always translate into more efficient or intuitive behaviour in practice. While subjective impressions are important for acceptance, further research is needed to align design intuitiveness with actual real-world performance.

5.2.3 User experience in VR experiment

The participants were asked to evaluate the realism of the VR experiment, the occurrence of simulator sickness symptoms and their overall level of presence within the virtual environment. Regarding the realism of the VR, participants reported a moderate to high rating for visuals (mean = 3.48), AV behaviour (mean = 3.61) and bicycle movement (mean = 3.65). The background audio received the lowest rating (mean = 2.87), likely due to its limited role in the experiment. The sound was not essential for task performance, but was merely included to enhance immersion. When averaged across all aspects, the overall score of the realism received a mean of 3.40, indicating that participants generally perceived the VR as sufficiently realistic. This score is comparable with results from existing literature employing VR as research method in similar contexts. For instance, Feng, Farah, and Arem (2023) reported an overall realism rating of 3.68 in a VR study of pedestrian-AV interactions, and Feng, Duives, and Hoogendoorn (2022) found an average rating of 4.04 in a VR study of way-finding behaviour in multi-story buildings. Therefore, the realism ratings are within expected ranges and support the validity of using VR as research method for studying cyclist-AV interactions.

In the SSQ, the participants evaluated symptoms of simulator sickness after completing the VR experiment. The SSQ is divided into three subscales of which the highest rating was observed for disorientation (mean = 30.09), and the lowest for oculomotor (mean = 16.14). The total score of the SSQ averaged a score of 25.09, suggesting a low to moderate level of simulator sickness, while remaining within expected ranges for VR studies. For comparison, similar studies reported total SSQ scores of 28.40 (Feng, Farah, and Arem, 2023) and 15.06 (Feng, Duives, and Hoogendoorn, 2022). While the results in this study are comparable with those of existing literature, they may be higher due to the cyclist-based setup of the experiment. In contrast to pedestrian VR experiments, cycling requires ongoing movement and balance coordination, which are not fully replicated in virtual environments. This mismatch between visual input and physical sensation can lead to greater sensory conflict, potentially resulting in higher simulator sickness scores.

The PQ was used to evaluate how strongly the participants felt a sense of presence while engaging in the VR experiment. It consisted of four sub-scales, of which the level of immersion received the highest ratings (mean = 2.69) suggesting that participants generally felt well-integrated and immersed in the virtual environment. The interface quality received the lowest rating (mean = 1.56), indicating that some participants may have experienced difficulties when interacting with the VR system. While the PQ was administered using a 3-point Likert scale in this study, most other studies used a 7-point Likert scale. The results, however, can still be useful and cautious comparisons can be made to get an idea of the level of presence in the VR experiment. For example, existing VR studies reported average PQ scores of 4.43 (Tran and Parker, 2024), 4.59 (Velasco et al., 2019) and 4.47 (Nuñez Velasco et al., 2020). These are all rated on a 7-point scale which equates to around 63-66% of the maximum score. The overall PQ rating in this study averaged 2.16 out of 3, which equates to 72%. The ratings therefore suggest that the participants experienced a moderately high level of presence in this experiment, and it falls in line with expected ranges, even scoring slightly higher.

When considering the results from the realism, simulator sickness and presence questionnaires, it can be concluded that the VR experiment was sufficiently realistic and immersive for the context of this study, supporting the use of VR as a valid research method in examining cyclist-AV interactions. However, based on personal observations made during the experiment sessions, some participants displayed irregular or unexpected cycling behaviour which may not fully reflect real-world responses. For instance, some participants made overly confident crossing decisions, showed sudden accelerations or lacked a natural and continuous movement throughout the scenarios. This could be due to a reduced sense of risk or consequence in the virtual environment. It is also possible that some participants perceived the experience more as a game, resulting in different behaviour compared to real traffic situations. However, this only applied to a select number of participants, as the majority of the participants displayed normal or expected behaviour. Therefore, while the results offer valuable insights into cyclist behaviour and the VR environment generally succeeded in generating realistic responses, some caution is warranted when directly applying the findings to real-world implications.

5.2.4 Answering the research questions

Sub-question 1: What is theoretically the impact of different eHMIs on the crossing behavior of cyclists?

The conceptual model explained in Section 2.5, developed from the literature review, provides an answer to the first sub-question of this study. It proposed that the use of any eHMI leads to more effective and efficient cyclist behaviour as it increases the crossing intentions, perceived safety and trust in AVs, while decreasing the gazing time and crossing initiation time. Out of the proposed eHMI designs, textual eHMIs are generally clearer and more persuasive than non-textual eHMIs (Bazilinskyy, Dodou, and De Winter, 2019). Therefore, it was hypothesized that the textual eHMI would have the strongest positive effect on cyclists' crossing behaviour. Symbolic eHMIs were expected to produce moderately positive effects, but may require more time to interpret. Light-based eHMIs were expected to have the weakest effect, given their potential ambiguity and need for prior learning.

Sub-question 2: How are objective aspects of cyclists' crossing behaviour empirically affected by different eHMI designs in a shared space in a VR experiment?

The findings from the experimental data partially support the theoretical claims derived from the literature review. Specifically, the presence of any eHMI appears to influence the crossing behaviour of cyclists. For instance, text- and light-based eHMIs significantly reduced the crossing initiation times compared to not using an eHMI, therefore enabling quicker decision-making. Additionally, when the AV is not yielding to the cyclist, the light-based eHMI increased the crossing time and gazing time of the cyclists, suggesting difficulties in quickly interpreting the interface. Lastly, no consistent effects were observed for any of the other behavioural measures such as the crossing intention and speed change.

Sub-question 3: How are subjective aspects of cyclists' crossing behavior—such as perceived risk, safety and trust in the AV—affected by different eHMI designs in a shared space in a VR experiment?

The subjective data gathered from the post-experiment questionnaire revealed a strong and consistent preference for all eHMI designs compared to having no eHMI, increasing aspects like the perceived safety, trust in AV and decision-making of the cyclists. Furthermore, among the different eHMI types, the symbolic design received the best ratings across all subjective measures, such as perceived risk, safety and trust in the AV, followed by the textual and then light-based display. The differences between the three designs, however, were not significant enough to definitively conclude that one is better perceived or more preferred over the others.

Main research question: What is the effect of different eHMIs on cyclists' crossing behavior when interacting with AVs?

Overall, the presence of any type of eHMI is shown to enhance cyclist-AV interactions as it enables quicker decision-making and is strongly preferred over no form of communication. Its impact, however, is not uniform over all behavourial measures, since there seems to be a stronger influence on cyclists' subjective perceptions than on their behavourial actions. Furthermore, the differences between the effects of the three eHMIs (textual, symbolic and lights) on cyclists' crossing behaviour appear to be minimal. The experimental data shows that text-based eHMIs seem to be capable of providing the most clear-cut instructions in terms of behavior, while symbolic eHMIs are best perceived by the users. This gap between perceived and actual usability suggests that eHMIs can be a promising addition to AV communication methods, although further refinement of the overall designs, including improving intuitiveness and reducing ambiguity, is necessary to achieve their potential for real-world deployment.

5.3 Limitations of the research

The study that has been conducted provided valuable insights into the effects of different eHMIs on cyclists' crossing behaviour when interacting with an AV in a shared space. However, it also brings certain limitations that should be acknowledged to contextualize the results and support future research. First of all, the VR setup, including the virtual environment and the bicycle simulator, introduced certain constraints. The visual quality of the VR headset was not always optimal, mainly due to possible limitations of the hardware. This may have affected how clearly the participants were able to see and interpret the eHMI designs. By using higher resolution and more advanced VR equipment, this issue could be addressed in future studies. Additionally, the bicycle simulator lacked some features such as steering and natural bike handling, which may have influenced participants' behaviour.

Furthermore, while VR offers a realistic and immersive simulation of real-world traffic scenarios within a safe and controlled environment, behaviour exhibited in a virtual setting may not fully reflect how people would act in actual real-life situations. This can be attributed to a lack of real physical consequences, the artificiality of the environment and a reduced sense of urgency or risk. Participants may feel less risk and behave more recklessly than in actual traffic scenarios, as they are aware the simulation poses no real danger. Therefore, while the findings of such VR experiments produce valuable observations and behavioural trends, they should be reservedly interpreted and applied to the real-world.

The traffic scenarios and AV interactions used in this study also present certain limitations, as they are simplified to isolate the effects of main variables. Even though this enhances experimental control, real-world traffic scenarios are much more complex and unpredictable, since they often include multiple road users and dynamic interactions. Moreover, environmental factors were not taken into account, such as road elevation or weather conditions, which can also influence decision-making and overall behaviour of cyclists.

Another limitation lies in the simplicity of the eHMI designs that have been tested. This study was limited to the evaluation of four basic visual eHMI designs, while more complex and adaptive designs remain unexplored. More advanced designs might offer improved clarity, intuitiveness and adaptability to different scenarios. Other modes of eHMIs, such as haptic or auditory eHMIs, could also be explored as promising alternatives or additions to visual cues.

An additional limitation of this study lies in the demographics of the participants as mainly students and employees of TU Delft were recruited. This group generally tends to be more familiar with concepts such as AVs, VR and eHMIs, which potentially influences their behaviour. It can make them more confident or accepting of the technology, therefore allowing them to interpret the messages more easily compared to the general public. Furthermore, from observations made during the experiment, a difference in behaviour was noticed between Dutch participants, who tend to have a lot of cycling experience, and non-Dutch participants, or those who generally have less experience with cycling. For example, Dutch participants tended to cycle faster and more assertively compared to non-Dutch participants, who generally were more cautious and reserved. Similar differences were observed between male and female participants, where male participants generally demonstrated a more assertive cycling style. These behavioural differences could influence how participants respond to the eHMIs.

Last of all, the way in which some target variables are defined could also pose limitations. Several metric definitions, such as the crossing initiation time, crossing time and speed change, rely on the use of certain thresholds that are estimated based on observed patterns or assumptions. Even though such thresholds were chosen to reflect realistic and consistent behaviour, they are ultimately approximations and not standardized metrics. Therefore, minimal differences in these threshold values could lead to different measurements and statistical outcomes. This indicates the sensitivity of the findings and suggests examining their robustness by systematically testing various threshold values.

5.4 Recommendations for further research

Based on the findings and limitations of this study, several recommendations can be made to support future research and contribute to a more comprehensive understanding of eHMI use in cyclist-AV interaction. First of all, the range of the tested scenarios can be expanded. While this study focused solely on crossing situations, it is essential to study other types of traffic scenarios to evaluate how interactions and cyclist behaviour differs across various situations. The usefulness of different eHMI designs and the type of information that needs to be displayed may depend on the complexity of the situations, spatial layout and the decisions the cyclist has to make. Furthermore, real-world situations often involve interactions with multiple road users, adding complexity and influencing the way eHMIs are interpreted. When encountering more than one road user, it might become unclear which individual the AV is communicating with. Therefore, these situations require further investigation to evaluate how different eHMI designs perform and are perceived in more dynamic environments.

Another area of research that can be explored, is examining the effect of alternative eHMI designs and modalities, such as haptic or auditory feedback, on cyclists crossing behaviour. Even the use of multi-modal eHMIs, which combines visual, auditory or haptic cues, can be investigated to see whether they improve the clarity and effectiveness in conveying intentions of the AV. Additionally, the visual designs that have been used in this study could be expanded or refined to improve clarity and intuitiveness. For instance, alternative textual messages could be investigated, such as egocentric versus allocentric messaging. Research on pedestrian-AV interaction have already shown that these differences have a significant impact on message interpretation. Moreover, the use of different symbols, animations or color schemes may also affect how cyclist interpret AV's intentions. The placement of the eHMIs on the AV is another way of changing the interface designs, which could increase the visibility and influence how they are perceived. This is another possible avenue for future research.

The participants' demographics of this study consisted primarily of students and staff members of TU delft, which may be more knowledgeable and exposed to the concept of AVs. This familiarity may allow for quicker understanding and interpretation of the intentions of AVs. Future research should therefore explore how different demographic characteristics, such as age, gender or familiarity with the concepts of AVs and eHMIs, influence the behaviour of cyclists and the way they interpret and perceive different eHMI designs. This identifies whether certain population groups require tailored forms of communication in order to make sure that AV systems are inclusive and intuitive for all road users. A specific demographic group that could benefit from further investigation is individuals with sensory impairments, such as those who are blind, deaf or colorblind. For example, eHMIs that rely solely on color-based signals could pose challenges for colorblind people. Similarly, individuals with hearing or visual impairments could benefit from multi-modal eHMIs that incorporate both visual and auditory feedback. Therefore, future research should explore how eHMI designs can be adapted to accommodate these users to ensure safe interaction with AVs for all road users.

6 Conclusion

The aim of this study was to examine the effect of different eHMI designs on cyclists' crossing behaviour when interacting with an AV in a shared space area. To investigate this, a VR experiment was conducted in which participants used a bicycle simulator and encountered an AV in a series of controlled crossing scenarios. Four eHMI designs (no eHMI, textual, symbolic, lights) were tested to allow for comparative analysis. The experimental data was used to analyze objective metrics of cyclists' crossing behaviour, including measures as crossing initiation time, crossing time, speed change, gazing time and crossing intentions. A post-experiment questionnaire was conducted to capture data on subjective measures such as perceived risk, trust in AV and clarity of the eHMIs.

The findings of the study showed that the use of any eHMI does influence cyclist crossing behaviour, however the effects are not consistent across all behavioural metrics. When the AV is yielding, the textual and light-based eHMIs significantly improved the crossing initiation time compared to using no eHMI. The light-based eHMI, on the other hand, significantly increased the crossing time and gazing time when the AV was not yielding. For the other objective measures, no significant effects were observed between the different eHMI conditions. In contrast, the subjective measures did strongly indicate that the presence of any eHMI is preferred, as it significantly improved the perceived safety, trust in AV and decision-making of the cyclists, suggesting its importance in real-world implications. Identifying which eHMI design is the most efficient and effective in enhancing communication proved to be somewhat inconclusive. While symbolic eHMIs were strongly preferred by participants and received the highest ratings on all subjective measures compared to the other eHMIs, the objective behavioural data did not necessarily support this. Therefore, a gap is observed between the perceived clarity of eHMIs and actual behaviour of the cyclist. Although this may be partly due to the limitations of this study, it also highlights the need for further research to ensure that eHMI designs do not only feel intuitive but also effectively support behavioural responses.

The significance of this study lies in its contribution to understanding both the potential and challenges of effectively implementing eHMIs into real-world applications to support interactions between VRUs, in particular cyclists, and AVs. As AV technology continues to advance and becomes an integral part of urban transport and mobility in the near future, it is essential to ensure safe interaction and efficient communication with other road users. Since AVs lack human drivers, traditional social cues are no longer available, which is why the use of eHMIs are proposed to bridge this communication gap. Therefore, eHMI design must be intuitive, universal and adaptable to complex and dynamic real-world situations. This study contributes to this development by highlighting the benefits and limitations of current eHMI designs, and emphasizing the need to develop inclusive and robust eHMIs.

The key limitations of this study must be acknowledged and consist of the simplification of both the tested traffic scenarios and eHMI designs. As real-world traffic scenarios often involve multiple road users, the interactions are far more complex and unpredictable. Additionally, the eHMI designs only consisted of visual displays, and do not provide any insights into the potential of alternative designs, such as auditory, haptic or multi-modal signals. Future research should therefore expand the range of tested scenarios to understand how eHMIs are perceived in more complex situations, and investigate alternative eHMI designs to ensure more inclusive and intuitive communication.

Overall, this study contributes to the growing literature on cyclist-AV interactions by providing empirical insights of how cyclists perceive and respond to different types of eHMIs. It supports the assumption that eHMIs play an important role in improving communication between cyclists and AVs, increasing perceived safety and trust in AVs. Moreover, it provides a basis for further research aimed at refining and optimizing eHMI designs for real-world employment.

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Appendix

Appendix A: Post-Experiment Questionnaire

Post-Experiment Questionnaire

14 mei 2025

Thank you for participating in this Virtual Reality experiment. This questionnaire is designed to gather insights into your experiences and perceptions of various parts of the VR simulation. Please answer honestly—there are no right or wrong answers! Your input will remain anonymous and will be used for research purposes only.

* Vereist

Part 1: Personal characteristics

1. Participant's ID (Filled in by researcher) *

2. Gender *

◯ Male

◯ Female

3. Age *

4. What is your previous experience with Virtual Reality (VR)? *

- No experience
- Little experience
- Average experience
- A lot of experience
- Expert

5. Before the experiment, how familiar were you with the concept of Automated Vehicles (AVs)? *

- Not at all familiar
- A little familiar
- Moderately familiar
- Quite familiar
- Very familiar

6. Before the experiment, how familiar were you with the concept of external Human-Machine Interfaces? *

- Not at all familiar
- A little familiar
- Moderately familiar
- Quite familiar
- Very familiar

7. How often do you ride a bicycle? *

- Less than once a week
- 1-2 days a week
- 3-5 days a week
- Every day

Part 2: Realism of the virtual environment

8. Answer the questions below about the realism of the VR simulation.

	Not at all	Slightly	Moderate	Very	Extremely
How realistic did the visuals (e.g. objects, vehicles, environment) of the VR simulation feel?	◯	◯	◯	◯	◯
How realistic did the behaviour of the automated vehicle (e.g., speed, movement, yielding) feel?	◯	◯	◯	◯	◯
How realistic did the movement of the bicycle feel?	◯	◯	◯	◯	◯
How realistic did the background audio feel?	◯	◯	◯	◯	◯

Part 3: Simulator Sickness Questionnaire (SSQ)

9. How much is each of the following symptoms below affecting you right now?

	None	Slight	Moderate	Severe
General discomfort	◯	◯	◯	◯
Fatigue	◯	◯	◯	◯
Headache	◯	◯	◯	◯
Eye strain	◯	◯	◯	◯
Difficulty focusing	◯	◯	◯	◯
Salivation increasing	◯	◯	◯	◯
Sweating	◯	◯	◯	◯
Nausea	◯	◯	◯	◯
Difficulty concentrating	◯	◯	◯	◯
Fullness of head	◯	◯	◯	◯
Blurred vision	◯	◯	◯	◯
Dizzy (eyes open)	◯	◯	◯	◯
Dizzy (eyes closed)	◯	◯	◯	◯
Vertigo	◯	◯	◯	◯
Stomach awareness	◯	◯	◯	◯
Burping	◯	◯	◯	◯

Part 4: Presence Questionnaire

10. Answer the following questions below.

	Not at all	Somewhat	Completely
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 (bicycle simulator)?	◯	◯	◯
How much did your experience in the virtual environment seem consistent with your real-world experience?	◯	◯	◯
Were you able to anticipate what would happen next in response to the actions that you performed?	◯	◯	◯
How involved were you in the virtual environment experience?	◯	◯	◯
How quickly did you adjust to the virtual environment?	◯	◯	◯
How much delay did you experience between your actions and expected outcomes?	◯	◯	◯
How much did the control devices interfere with the performance of assigned tasks or with other activities?	◯	◯	◯

	Not at all	Somewhat	Completely
How much did the visual display quality interfere or distract you from performing assigned tasks or required activities?	◯	◯	◯
How completely were you able to actively survey or search the environment using vision?	◯	◯	◯
How proficient in moving and interacting with the virtual environment did you feel at the end of the experience?	◯	◯	◯
How compelling was your sense of moving around inside the virtual environment?	◯	◯	◯
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 well could you examine objects from multiple viewpoints?	◯	◯	◯
How much did the auditory aspects of the environment involve you?	◯	◯	◯
How well could you identify sounds?	◯	◯	◯

Part 5: Perceived risk and trust in AV

11. Answer the questions below about your perceived risk.

	No risk at all	Slight risk	Moderate risk	High risk	Extremely high risk
How much risk did you feel while interacting with the AV when not using any eHMI?	◯	◯	◯	◯	◯
How much risk did you feel while interacting with the AV when using a textual eHMI?	◯	◯	◯	◯	◯
How much risk did you feel while interacting with the AV when using a symbolic eHMI?	◯	◯	◯	◯	◯
How much risk did you feel while interacting with the AV when using lights as eHMI?	◯	◯	◯	◯	◯

12. Answer the questions below about your perceived safety.

	Not at all safe	Slightly safe	Moderately safe	Very safe	Extremely safe
How safe did you feel interacting with the AV when not using any eHMI?	◯	◯	◯	◯	◯
How safe did you feel interacting with the AV when using a textual eHMI?	◯	◯	◯	◯	◯
How safe did you feel interacting with the AV when using a symbolic eHMI?	◯	◯	◯	◯	◯
How safe did you feel interacting with the AV when using lights as eHMI?	◯	◯	◯	◯	◯

13. Answer the questions below about trust in the AV.

	No trust at all	Slight trust	Moderate trust	High trust	Complete trust
How much did you trust the AV to behave predictably and safely when not using any eHMI?	○	○	○	○	○
How much did you trust the AV to behave predictably and safely when using a textual eHMI?	○	○	○	○	○
How much did you trust the AV to behave predictably and safely when using a symbolic eHMI?	○	○	○	○	○
How much did you trust the AV to behave predictably and safely when using lights as eHMI?	○	○	○	○	○

Part 6: Preferences regarding eHMI design

14. Answer the questions below about the clarity of the eHMI designs.

	Not at all clear	Slightly clear	Moderately clear	Very clear	Extremely clear
How clearly did you understand the AV's intentions when not using any eHMI?	◯	◯	◯	◯	◯
How clearly did you understand the AV's intentions when using a textual eHMI?	◯	◯	◯	◯	◯
How clearly did you understand the AV's intentions when using a symbolic eHMI?	◯	◯	◯	◯	◯
How clearly did you understand the AV's intentions when using lights as eHMI?	◯	◯	◯	◯	◯

15. Answer the questions below about decision-making.

	Not at all easy	Slightly easy	Moderately easy	Very easy	Extremely easy
How easy was it to decide whether to cross when the AV is not using any eHMI?	◯	◯	◯	◯	◯
How easy was it to decide whether to cross when the AV is using a textual eHMI?	◯	◯	◯	◯	◯
How easy was it to decide whether to cross when the AV is using a symbolic eHMI?	◯	◯	◯	◯	◯
How easy was it to decide whether to cross when the AV is using lights as eHMI?	◯	◯	◯	◯	◯

16. Answer the questions below about your preferences of the eHMI designs.

	Least preferred	Slightly preferred	Neutral	Strongly preferred	Most preferred
How much do you prefer the use of no eHMI compared to the others?	◯	◯	◯	◯	◯
How much do you prefer the use of a textual eHMI compared to the others?	◯	◯	◯	◯	◯
How much do you prefer the use of a symbolic eHMI compared to the others?	◯	◯	◯	◯	◯
How much do you prefer the use of lights as eHMI compared to the others?	◯	◯	◯	◯	◯

Appendix B: Post-hoc pairwise comparisons

Table 19: Post-hoc pairwise comparisons for crossing initiation time ("Yielding" condition, Tukey-adjusted)

Contrast	Estimate	SE	t	p
No eHMI - Textual	0.447	0.146	3.063	0.013
No eHMI - Symbolic	0.188	0.148	1.275	0.580
No eHMI - Lights	0.444	0.149	2.976	0.017
Textual - Symbolic	-0.258	0.149	-1.735	0.309
Textual - Lights	-0.003	0.150	-0.021	1.000
Symbolic - Lights	0.255	0.152	1.681	0.337

Table 20: Post-hoc pairwise comparisons for crossing initiation time ("Not Yielding" condition, Tukey-adjusted)

Contrast	Estimate	SE	t	p
No eHMI - Textual	0.168	0.147	1.138	0.667
No eHMI - Symbolic	0.290	0.143	2.027	0.182
No eHMI - Lights	0.174	0.143	1.211	0.621
Textual - Symbolic	0.122	0.146	0.838	0.836
Textual - Lights	0.006	0.146	0.042	1.000
Symbolic - Lights	-0.116	0.142	-0.819	0.845

Table 21: Post-hoc pairwise comparisons for perceived risk (Tukey-adjusted)

Contrast	Estimate	SE	z	p
No eHMI - Textual	3.059	0.599	5.104	<0.001
No eHMI - Symbolic	3.222	0.603	5.341	<0.001
No eHMI - Lights	2.182	0.552	3.954	<0.001
Textual - Symbolic	0.163	0.514	0.317	0.989
Textual - Lights	-0.878	0.520	-1.688	0.330
Symbolic - Lights	-1.040	0.515	-2.021	0.180

Table 22: Post-hoc pairwise comparisons for perceived safety (Tukey-adjusted)

Contrast	Estimate	SE	z	p
No eHMI - Textual	-2.147	0.524	-4.101	<0.001
No eHMI - Symbolic	-2.913	0.557	-5.232	<0.001
No eHMI - Lights	-1.861	0.525	-3.546	<0.001
Textual - Symbolic	-0.766	0.478	-1.603	0.377
Textual - Lights	0.287	0.482	0.595	0.934
Symbolic - Lights	1.052	0.498	2.113	0.149

Table 23: Post-hoc pairwise comparisons for trust in AV (Tukey-adjusted)

Contrast	**Estimate**	**SE**	**z**	**p**
No eHMI - Textual	-2.938	0.568	-5.168	<0.001
No eHMI - Symbolic	-3.291	0.580	-5.676	<0.001
No eHMI - Lights	-2.441	0.552	-4.419	<0.001
Textual - Symbolic	-0.354	0.470	-0.753	0.875
Textual - Lights	0.496	0.479	1.036	0.728
Symbolic - Lights	0.850	0.481	1.769	0.289

Table 24: Post-hoc pairwise comparisons for clarity of eHMIs (Tukey-adjusted)

Contrast	**Estimate**	**SE**	**z**	**p**
No eHMI - Textual	-4.671	0.751	-6.538	<0.001
No eHMI - Symbolic	-5.471	0.769	-7.116	<0.001
No eHMI - Lights	-4.069	0.681	-5.977	<0.001
Textual - Symbolic	-0.800	0.488	-1.639	0.356
Textual - Lights	0.602	0.480	1.254	0.592
Symbolic - Lights	1.402	0.504	2.783	0.028

Table 25: Post-hoc pairwise comparisons for decision-making (Tukey-adjusted)

Contrast	**Estimate**	**SE**	**z**	**p**
No eHMI - Textual	-3.537	0.606	-5.832	<0.001
No eHMI - Symbolic	-4.107	0.635	-6.465	<0.001
No eHMI - Lights	-3.037	0.590	-5.152	<0.001
Textual - Symbolic	-0.570	0.475	-1.202	0.626
Textual - Lights	0.499	0.488	1.023	0.736
Symbolic - Lights	1.070	0.500	2.139	0.141

Table 26: Post-hoc pairwise comparisons for preferences regarding eHMI design (Tukey-adjusted)

Contrast	**Estimate**	**SE**	**z**	**p**
No eHMI - Textual	-3.8074	0.660	-5.765	<0.001
No eHMI - Symbolic	-4.7024	0.694	-6.776	<0.001
No eHMI - Lights	-3.7341	0.652	-5.725	<0.001
Textual - Symbolic	-0.8950	0.464	-1.929	0.216
Textual - Lights	0.0733	0.461	0.159	0.999
Symbolic - Lights	0.9683	0.464	2.087	0.157