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Coordinating Internal and External HMIs for Cooperative Driver-Pedestrian Situation Resolution

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Abstract

Traffic interactions between vehicles and pedestrians are inherently uncertain due to the dynamic nature of the interaction partners' behavior. Resolutions require mutual understanding of the situation and each other's intention, typically achieved through explicit and implicit communication. Assistance systems with internal or external HMIs can reduce uncertainty for drivers or pedestrians, but joint resolution requires combining both types with reasoning mechanisms to coordinate them. We propose a cooperative system that coordinates traffic interactions by communicating to both driver and pedestrian. The system analyzes the traffic situation, calculates cooperative behavior options, derives recommendations for each partner, and harmonizes external and internal signals. We evaluated the system in a multiplayer virtual reality experiment, pairing pedestrians and drivers in unsignalized crossing situations. Results showed significantly more interactions resolved by pedestrian crossing first, with drivers showing stronger, earlier yielding cues that let pedestrians initiate crossing faster. Additionally, the external HMI enhanced perceived driver yielding.

Keywords— Vehicle-Pedestrian Interactions, Human-Machine-Interfaces, Advanced Driver Assistance Systems, Decision Making, Human Factors

1 Introduction

Interactions between pedestrians and vehicles are usually ambiguous regarding the intentions of the traffic participants and, eventually, the resolution of the situation. Interactions are often not only guided by traffic rules but rather following informal rules or social norms (Dey and Terken, 2017; Rasouli and Tsotsos, 2020; Schneemann and Gohl, 2016; Sucha et al., 2017). Following Markkula et al. (2020), interaction implies a conflict between the interacting agents for the same region of space. Thus, the resolution of a traffic interaction is characterized by the negotiation of the traffic participants for the order of passing to avoid inefficient behavior or even collisions (Habibovic et al., 2018; Markkula et al., 2020). Successfully negotiating the order of passing requires the interaction partners to develop a mutual understanding of the situation (Domeyer et al., 2020). They need to cooperate with each other to achieve a joint resolution. Within a cooperation, communication is an important means to convey information about the own intention or the expected behavior of the interaction partner. Communication can be implicit or explicit. Implicit communication means information exchange that is conveyed through one's behavior and motion, and can happen both intentionally as well as unconsciously. The awareness of the messages conveyed through the own actions and the ability to perceive and interpret the other agent's behavior play a crucial role for coordination ("Behavioral Implicit Communication") (Castelfranchi et al., 2012).

Explicit communication refers to any type of signaling or transmission of information that does not affect the own behavior (Markkula et al., 2020; Rasouli and Tsotsos, 2020). Explicit communication through human-machine interfaces (HMIs) has been proposed in assistance systems supporting traffic interactions (Bengler et al., 2020; Dey et al., 2020; Schieben et al., 2019).

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Such HMIs are used to inform traffic participants inside or outside of a vehicle about a traffic situation. HMIs are an active field of research as they offer a possibility to overcome current limitations of communication between road users (Habibovic et al., 2018; Man et al., 2025; Rouchitsas and Alm, 2019). HMIs enable early interaction resolutions, which can improve traffic flow and enhance the perceived safety of pedestrians, thereby creating an overall benefit for all traffic participants (Bellet et al., 2022; Dietrich et al., 2020). However, novel communication systems should be considered as an enhancement of the interaction rather than a replacement for existing modes of communication. Most studies that investigate external HMIs (eHMIs), focus on the support of external road users in interactions with automated vehicles (AVs). In this paper, we propose an advanced driver assistance system (ADAS) which takes communication with both interaction partners into account explicitly. Thereby, the system aims at facilitating cooperative behavior, while both agents remain in control and responsible for their actions.

1.1 Background

Due to the asymmetric vulnerability in vehicle-pedestrian interactions, drivers are expected to contribute a particularly large share to the resolution of an interaction. However, studies have demonstrated uncertainty in traffic interactions regarding the outcome and the ambiguity of the interaction partners' intentions. Varhelyi (1998) observes adversarial driver behavior in interactions with pedestrians at zebra crossings indicating competitive behavior for passing order. Sucha et al. (2017) investigate interactions between human drivers and pedestrians at crosswalks showing that drivers fail to yield in 36% of all observed interactions despite their obligation to give right of way to pedestrians. Dey and Terken (2017) confirm this finding showing that 25.4% of drivers still assert their own priority even if a pedestrian has already stepped into the far lane at a crosswalk. The authors argue that it seems to be common practice and such driver behavior is accepted by the crossing pedestrians. Sucha et al. (2017) also point out a possible mismatch in the perception of human drivers regarding their own yielding behavior in interactions with pedestrians. Contrary to the empirical results of the observational studies that unveil that drivers often fail giving right of way, human drivers state that they would yield to pedestrians at a crosswalk always or at least very often. The discrepancy between the observed behavior and the subjective evaluation of one's behavior highlight the necessity for communication in vehicle-pedestrian interactions.

1.1.1 Importance of communication cues for human drivers

Several studies have investigated interactions between human drivers and pedestrians examining their decision making and the role of communication (Beggiato et al., 2017; Dietrich et al., 2020; Domeyer et al., 2020; Haq et al., 2024; Lee et al., 2021; Pekkanen et al., 2022; Rasouli and Tsotsos, 2020; Schneemann and Gohl, 2016; Sucha et al., 2017; Tian et al., 2023; Varhelyi, 1998). When deciding whether to yield, drivers usually make use of environmental cues and signals related to the interaction with the pedestrian (Chen et al., 2019; Schmidt and Faerber, 2009). Environmental cues entail information about the properties of the road, e.g., road width, number of lanes, or speed limits. Other environmental cues such as the presence of road signs, crosswalks, or traffic lights convey information regarding the priority. Implicit signals such as the pedestrian's motion and gaze, social cues such as group dynamics, as well as proximity and posture relative to the road are important factors to estimate a pedestrian's intention (Melo Castillo et al., 2025; Moreno et al., 2023; Rasouli et al., 2017b). A special role can be attributed to explicit communication through eye contact or gazing since it can be used to communicate multiple means, such as the perception of other road users or the acknowledgment of their intention (Rasouli and Tsotsos, 2020; Schneemann and Gohl, 2016; Sucha et al., 2017). However, perceiving the relevant information cues can be challenging, especially at large distances. Hence, drivers could benefit from additional timely information provided by an ADAS that offers assistance and guides them in a traffic interaction.

1.1.2 Pedestrian crossing decision models

The decision making process of pedestrians in crossing situations and the interplay between pedestrian and vehicle has been explored extensively (Markkula et al., 2023; Petzoldt, 2014; Schroeder et al., 2014). Schroeder et al. (2014) propose a two-stage model to describe the decision making process of pedestrians. In the first stage of this model, a pedestrian makes a crossing decision based on the estimated time gap, which plays a major role in the decision making process of pedestrians (Beggiato et al., 2017; Petzoldt, 2014; Rasouli et al., 2017a; Sun et al., 2003; Wang et al., 2010). The time gap τ describes the time until the vehicle reaches the pedestrian if it continues driving with the current velocity and is also referred to as time-to-arrival (TTA) or time-to-collision (TTC). If a situation is resolved in the early stage, the pedestrian assumes the initiative to cross based on the kinematic characteristics of the situation independent of the vehicle behavior. In this phase, no cooperation is necessary. According to the model proposed by Schroeder et al. (2014), if a pedestrian rejects a gap and decides not to cross in the first stage, they enter the second stage, in which they look for clear yielding signals from the vehicle. This model leads to a bimodal distribution of crossing events, which has also been found in the studies by Haq et al. (2024); Lee et al. (2025); Tian et al. (2023): A first portion of crossings, so called "early crossings", happens in an early phase of the interaction. Another portion of crossing events, so called "late crossings", occur when the vehicle is close to the pedestrian showing clear yielding signs, or has already passed the pedestrian. Those crossing events can be attributed to the second stage of the decision making process. In this part of an interaction, communication between the driver and a pedestrian is particularly relevant to enable a cooperative resolution. Tian et al. (2025) propose a model that incorporates a hybrid perception strategy to describe the characteristics of pedestrian crossing decisions. In line with previous studies, the authors suggest that pedestrians make

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snap-shot decisions if the vehicle is not yielding. If implicit yielding cues become more apparent, pedestrians apply a dynamic decision strategy based on the visual cue $\dot{\tau}$. The model incorporates a hybrid perception strategy that accurately captures the mechanisms of the decision making in the two different stages including the transition between the two stages.

1.1.3 Influence of implicit and explicit communication on pedestrian behavior

Implicit communication has been found to be of significant importance in vehicle-pedestrian interactions. The own behavior should not only be understood as a means to reach a certain position, but it fulfills both the purpose of moving to a certain target as well as communicate a message about the own intention to other traffic participants Domeyer et al. (2022). Awareness of implicit communication is crucial because individuals inevitably convey signals through their own behavior (Mertens et al., 2020; Watzlawick et al., 2011). In the study of Lyu et al. (2025), the participants indicated that the implicit cues from the vehicle were the predominant factor for their crossing decision. Tian et al. (2023) investigate the influence of different deceleration patterns and vehicle speeds on pedestrians' crossing decisions and conclude that lower vehicle speeds are generally more likely to be interpreted as yielding intention. A finding that is also supported by the study of Schneemann and Gohl (2016). Moreover, Tian et al. (2023) show that early onset braking facilitates noticing a vehicle's yielding intention. Similarly, Dietrich et al. (2019) demonstrate that early braking reduces the time that pedestrians need to evaluate the vehicle behavior enabling earlier crossings. Tian et al. (2023) and Pekkanen et al. (2022) suggest that the implicit communication perceived by a pedestrian in an interaction with an oncoming vehicle is captured by the change rate of the time gap $\dot{\tau}$. Additionally, explicit communication cues can further help resolving ambiguous situations. Sucha et al. (2017) bring out an asymmetric need of drivers and pedestrians for establishing eye contact. In their study, 84% of pedestrians waiting to cross sought eye contact with the driver, whereas only 34% of drivers responded by seeking the pedestrians' eye contact. Other explicit signals such as hand signs or flashing the vehicle's headlights are found to be useful to contribute to a successful resolution (Sucha et al., 2017). However, those types of explicit signals are reported to occur only rarely (Dey and Terken, 2017; Lee et al., 2021). Based on their findings regarding the usage of eHMIs in interactions with AVs, Dey and Terken (2017) argue that explicit communication might be less crucial than one might intuitively assume. Rasouli et al. (2018), on the contrary, argue that explicit communication cues can be quite useful for resolving traffic interactions even though they are not frequently used. These contradicting interpretations emphasize the necessity for further exploration of the effects of explicit communication on vehicle-pedestrian interactions since pedestrians can possibly benefit from additional explicit information from the vehicle.

1.2 Related work

There have been prior efforts to support traffic participants in resolving interaction situations through communication. We will discuss approaches with a focus on vehicle-pedestrian interactions. One can find two major directions: Informing the driver about the outside situation through an internal HMI (iHMI), or providing information about the vehicle to the pedestrian using an external HMI (eHMI).

1.2.1 Internal HMIs

Internal HMIs are a suitable way to support the driver in handling general traffic situations. They have proven useful for alerting drivers and for communicating warnings in critical situations (Maag et al., 2015; Meng et al., 2015; Puphal et al., 2024). Bella et al. (2017) demonstrate that a timely iHMI warning about a crossing pedestrian leads to earlier braking for drivers that exhibit rather aggressive behavior otherwise. Moreover, iHMIs have been used as a way to inform passengers of an AV about the vehicle's state, intention, or next maneuvers (Beggiato et al., 2015; Bellet et al., 2022; Izquierdo et al., 2023; Li et al., 2021). However, the need for information provided by the vehicle has been found to vary depending on the automation level of the vehicle. The need is highest in partially automated driving (compared to manual driving and highly automated driving), where human drivers and the vehicle automation engage in shared execution of the driving task (Beggiato et al., 2015). Additionally, iHMIs have been used to explicitly support drivers' decision making. According to Kraft et al. (2019), ADAS integrating iHMIs to suggest options for cooperation are perceived as helpful. They show that with the help of the system, up to 98% of all traffic gaps were used by the cooperation partner. The results indicate that giving advice on how to behave in a cooperative situation can lower the costs of the driver giving right of way. Maag et al. (2022) compare variations of an iHMI communicating different levels of details about the surroundings of the vehicle, possible interaction partners and their cooperation capabilities, as well as instructions to resolve the situation. All variations aim at facilitating cooperative behavior. The results show that receiving information about the interaction partner, especially regarding their cooperation capabilities, is appreciated and perceived beneficial. Integrating iHMIs into ADAS offers a possibility to achieve synchronization between driver behavior and externally perceived communication, thus, facilitating cooperative behavior.

1.2.2 External HMIs

External HMIs have been an active area of research as well (Bengler et al., 2020; Dey et al., 2020; Habibovic et al., 2018; Man et al., 2025; Rouchitsas and Alm, 2019; Schieben et al., 2019). They can be used to convey additional explicit information from a vehicle to external road users, thus, they have the potential to assist pedestrians in interactions with vehicles. Communication modalities of eHMIs can comprise a variety of signals, such as visual messages (e.g., light signals, text messages), auditory

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signals (e.g., speech, abstract sounds), or vehicle-to-everything (V2X) signals transmitted from the vehicle to an external device (e.g., a signal sent to an external user's phone) (Dey et al., 2020; Lindner et al., 2022; Rouchitsas and Alm, 2019; Wessels et al., 2023). Most studies investigating the effect of eHMIs focus on interactions between pedestrians and AVs where the vehicle is not controlled by a human driver (Eisele et al., 2024; Liu and Bengler, 2025; Motamedi et al., 2026; Wilbrink et al., 2021). However, human drivers will remain integral part of road traffic in the foreseeable future. Thus, the requirements derived for communication in interactions between pedestrians and AVs should likewise be considered for ADAS that support human drivers in traffic interactions. The effectiveness of eHMIs is usually measured using objective metrics, such as the number of crossing events in front of the vehicle (Beggiato et al., 2017; Izquierdo et al., 2023; Lee et al., 2025; Wessels et al., 2023) or the crossing initiation delay (CID), which represents the time a pedestrian needs to make a crossing decision (Dietrich et al., 2020; Eisele et al., 2024; Lee et al., 2025; Wilbrink et al., 2021). Wessels et al. (2023) demonstrate an improved TTC estimation by pedestrians if a car emits an additional sound. Dietrich et al. (2020) and Wilbrink et al. (2021) show that using a visual eHMI to communicate the vehicle's intention reduces the CID of a pedestrian. Wilbrink et al. (2021) underline that the improvement using the eHMI can only be measured when displaying information about the vehicle intention. Confirming this result, Eisele et al. (2024) find that communicating only the vehicle's state of motion by displaying a message that represents the vehicle's braking status can lead to misinterpretation of vehicle behavior causing inappropriate crossing decisions. Using headlight flashing indicating that the vehicle intends to give right of way, Lee et al. (2025) find that an eHMI that pedestrians are familiar with facilitates crossing events in the phase between early and late crossings. Amann et al. (2024) assume a holistic perspective on vehicle-pedestrian interactions including the prediction of pedestrian behavior, planning cooperative vehicle behavior, and the activation of an eHMI. They demonstrate a mutual benefit for both interaction partners through joint actions.

Lyu et al. (2025) highlight the potential benefits of intuitive eHMIs on pedestrian-vehicle interactions. On the one hand side, well-designed eHMIs can reduce the number of visual fixations, thereby reduce the visual load during an interaction. On the other hand, the eHMI can contribute to shorter crossing initiation times and earlier crossing decisions, thereby enhance the efficiency of interactions. Brill et al. (2024) and Bellet et al. (2022) measure a significant increase in perceived safety when the interacting vehicle is equipped with an eHMI. Furthermore, Bellet et al. (2022) show that this improvement is particularly apparent when the projected stopping point of the vehicle is close to the pedestrian and when the vehicle also exhibits early deceleration behavior. Additionally, Dey et al. (2021) provide evidence that an eHMI communicating a vehicle's intention can enhance the willingness to cross. They conclude that the eHMI helps reducing perceived uncertainty. However, the authors also demonstrate that the eHMI does not affect the willingness to cross if the conveyed message differs from the intention that can be inferred from the vehicle behavior, concluding that pedestrians do not blindly follow the eHMI. It is a common finding that the effectiveness of the respective eHMI requires the vehicle behavior to match the eHMI message (Bellet et al., 2022; Dey et al., 2021; Eisele et al., 2024; Wilbrink et al., 2021). Izquierdo et al. (2025) demonstrate that both an eHMI reflecting the vehicle's intention as well as clear implicit communication can affect pedestrians positively. In their study, the eHMI increased the pedestrians' confidence in the vehicle and early gentle braking facilitated earlier pedestrian crossings compared to late and aggressive braking. However, when combining the eHMI with late braking behavior the positive effect of the eHMI could not be observed. Hence, a benefit of an eHMI is only measurable when the explicit message and the implicit communication are aligned. Amann et al. (2025) propose a strategy for optimal vehicle behavior planning considering the effects of the vehicle behavior on the pedestrian decision. Estimating the pedestrian reaction to the vehicle behavior unveils that ambiguous situations where the outcome is unclear require pronounced implicit communication to enable a cooperative resolution, which underlines the relevance of aligning eHMI signalization and vehicle behavior. Contrasting the previous studies, some studies raise concerns regarding the usability and effectiveness of eHMIs. Alvarez et al. (2019) and Clamann et al. (2017) don't find any measurable benefit related to the eHMI. In Lee and Daimon (2025), the participants show risk of overtrusting the external communication after multiple interactions with an eHMI, leading to possible unsafe behavior by crossing without looking at the surrounding lanes.

1.3 Research gap and contribution of this work

As elaborated in the preceding analysis of the state of the art, both eHMIs and iHMIs have been widely studied and an active field of research has emerged regarding their application in traffic interactions. Most studies focus on the design aspects of HMIs, neglecting the importance of the semantic context of a situation, such as the timing *when* to communicate, or the reasoning behind *what* to communicate. Studies have shown promising results regarding the positive effects of eHMIs on perceived safety and pedestrians' crossing behavior (Bellet et al., 2022; Brill et al., 2024; Dey et al., 2021; Wilbrink et al., 2021), however they often investigate the usage of eHMIs in interactions with AVs. Those studies cannot shed light to the implications that come with human drivers. For the application of eHMIs in human-driven cars it is inevitable to ensure that the driver behavior matches the externally communicated behavior to avoid misunderstandings which could lead to critical situations. Hence, they should be combined with driver monitoring and internal communication. Yet, studies mostly examine one type of HMI – either internal or external. Combining both types of communication (e.g., Bellet et al. (2022); Li et al. (2021)) is rarely considered as an opportunity to communicate to the driver and outside road users at the same time. Previous studies indicate a biased perception of drivers regarding their own behavior that often does not match the actual resolution. This mismatch illustrates the need to enhance cooperation and it brings out the potential of ADAS which integrate both iHMIs and eHMIs to coordinate the actions of the interacting traffic participants. Research has shown that the alignment of vehicle behavior and explicit communication plays a crucial role for the effectiveness of external communication. Hence, considering

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the interdependence between a driver's action and an eHMI as well as the interplay among the traffic participants is essential. This emphasizes the necessity for coordinated iHMI and eHMI actions that are suitable for the respective traffic situation.

In this paper, we present a cooperative HMI (cHMI) system that coordinates traffic interactions between the driver of a car and outside road users by communicating behavioral recommendations to them. The system utilizes both an iHMI and an eHMI and harmonizes their conveyed messages to enhance cooperation and reduce ambiguity of a traffic situation. The proposed system is agnostic of the design of the HMIs. For our evaluation study, we used prototypical symbols for both HMIs and participants received information about the symbols and their meaning beforehand. We did not evaluate the system regarding the HMI symbols or the overall HMI design. The ADAS integrates functionality to analyze the situation and understand the traffic participants' intentions. A cooperative behavior planner considers the joint costs of an interaction, i.e., the individual costs of both traffic participants. The holistic approach allows the cHMI to activate both iHMI and eHMI separately and in coordination with the recommended resolution as well as the behavior of each interaction partner. The cHMI extends the state of the art by using an eHMI in assisted driving where a human driver controls the vehicle, and synchronizing the eHMI with an iHMI. Another core contribution of this work is the full-system approach which enables adaptive HMI activations that take the recommended resolution, the behavior of the interaction partners, and their reaction to previous signals into account. We formulate the following research hypotheses that will be addressed in this paper.

- H1 The cHMI increases the number of cooperative situation resolutions in interactions between a human driver and a pedestrian that intends to cross the road.
- H2 The cHMI is well received and rated useful, and it is accepted by drivers and pedestrians.
- H3 The cHMI reduces the costs of a cooperative resolution.

2 Methodology

In this section, we will describe the methodology of our study including the setup of the virtual reality (VR) simulator and the test scenario, the study procedure and the recruitment process, as well as the system components that created the recommendations and communication signals for the driver and the pedestrian. We will also explain the measures that were used to analyze the data and evaluation of the proposed system.

2.1 Virtual reality (VR) simulation

We conducted a user study in a VR-simulator setup that allowed two participants, acting as driver and pedestrian, to interact with each other in the same environment (Aramrattana and Ochel, 2024). Distributed VR-simulators are regularly used to conduct user studies in a controlled environment (Lee et al., 2025; Liu and Bengler, 2025; Serrano et al., 2025; Tran and Parker, 2024). The setup consisted of two independent simulators, one for the driver and one for the pedestrian. The cHMI was integrated as another module of the simulator. All modules were connected to each other via a multiplayer server. User Datagram Protocol (UDP) was used to transmit data between the individual modules via the multiplayer server. The driving simulator enabled a realistic driving experience through the usage of a real steering wheel, throttle and brake pedals, and a vehicle dashboard. The level of immersion was enhanced by using a Varjo extended reality (XR)-3 headset through which the driver could see the virtual world as well as their own body and the vehicle components (steering wheel, pedals, dashboard). The pedestrian simulator consisted of a Varjo VR-3 headset and three HTC VIVE 3.0 trackers. They were used to track the pedestrian's motion, and allowed for a precise visualization of the pedestrian's movement and orientation in the virtual world. The visualization was based on Unreal Engine 5.2 using the MetaHuman plugin to animate the pedestrian. The pedestrian could move freely within a 6.5 m $\times$ 4 m area. Both simulators were equipped with headsets providing a realistic sound experience to the participants. This setup allowed for safe pedestrian-vehicle interactions. The cHMI module received data from both simulators about the states of the vehicle and the pedestrian, and generated iHMI and eHMI signals that fit the current traffic situation. These signals were transmitted to the simulators to visualize the respective HMI messages. Figure 1 depicts the setup of the distributed VR-simulator with all individual components.

2.2 Scenario

The driver drove through an urban area and repeatedly entered a single-lane, one-way road where the interactions with the pedestrian took place. The road width in the interaction zone was 4 m. After finishing an interaction, the pedestrian was "teleported" to the position where the next interaction with the driver would take place. Figure 2 depicts a birds-eye view of the section of the scenario where the interaction took place. While driving around, the driver encountered other vehicles or pedestrians, which were non-reactive and controlled according to fixed trajectories. The driver was not informed about which agents were non-reactive and which pedestrian agent represented the other participant. To arbitrate the interactions between the two participants and to create a more natural feeling for the pedestrian, we added cars that did not yield for the pedestrian. These "dummy" cars were not equipped with an eHMI and passed the pedestrian between two interactions. After interactions #1, #4, and #6, a dummy car was released approximately 7 s ahead of the driver to pass the pedestrian before the respective next interaction. The car drove at a constant speed of 40 km/h and was programmed not to stop for any pedestrian. Similarly, a few extra pedestrians, visible for both pedestrian and driver, were walking around on the side

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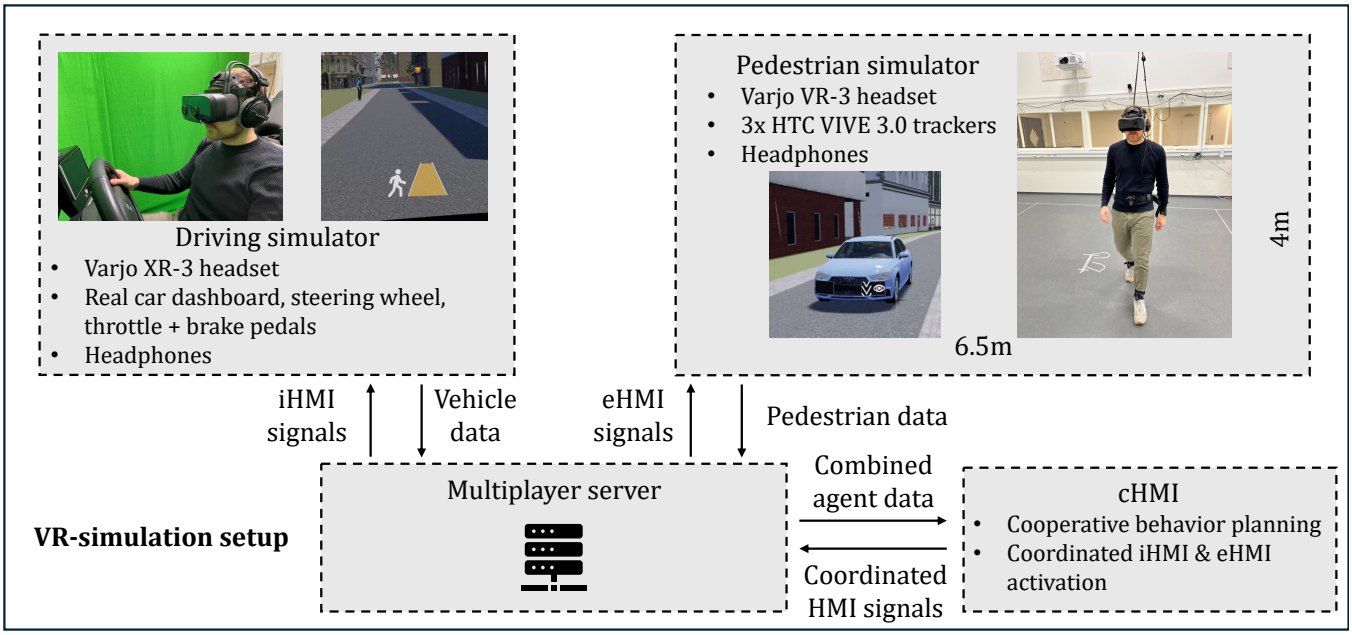

Figure 1: VR-simulator setup

walks. The dummy pedestrians did not cross the road. There were no traffic lights, zebra crossings, or other signs indicating the priority in this part of the road. Only a speed limit of 30 km/h was stated explicitly at the entrance of the one-way road. The selected scenario was designed to provide ambiguity for the interaction between the participants. On the one hand, the traffic situation was unsignalized, hence, in principle, the driver had the right of way and did not necessarily need to yield to the pedestrian. On the other hand, the interaction took place in an urban area, where pedestrian crossings were more likely to happen and could have been expected. We made this design choice that the default resolution determined by the traffic rules ("Vehicle first") differed from the initially desired cooperative resolution ("Pedestrian first"), since this setting allowed us to evaluate the effect of the cHMI on the cooperativity of the participants.

2.3 Participants

For the study, 35 pairs of drivers and pedestrians were recruited through online advertisements on social media and the homepage of the Swedish National Road and Transport Research Institute (institution of the 2nd and 6th author). Inclusion criteria were good vision and willingness to wear a VR-headset. Pedestrians were required to be able to walk without aid for



Figure 2: Birds-eye view on the scenario in the virtual world. The orange rectangle depicts the area in the one-lane road where the interaction took place.

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30 minutes and drivers were required to have a driver license to be eligible for participation. Susceptibility to motion sickness, epilepsy, or hearing loss were exclusion criteria. Besides these role-specific selection criteria, the participants could indicate which role they would prefer. The assignment was done based on their availability, their preferred role, as well as age and gender to make sure we had balanced test groups. All participants received a compensation of 800 SEK for their participation. In total, 47 participants identified as male and 23 identified as female. The mean age was 47.4 ($SD = 16.73$) years.

2.4 Study procedure

The study had a mixed within-between-subject design with the agent type as between-subject variable, i.e., each participant conducted experiments only as either pedestrian or driver within a random but fixed participant-pairing. The within-subject variable was the experimental condition (baseline vs. cHMI). Each participant pair conducted two experimental blocks each consisting of 8 interactions. The target of this study was to evaluate the overall system in comparison with unassisted, regular interactions. To limit the combinatorial complexity and the number of possible experiments for the participants, we did not conduct tests with either iHMI or eHMI only. 18 pairs did the test block in the baseline condition without the cHMI first, and 17 pairs started with the condition where the cHMI was available. After arriving at the test facilities, the participants received a short introduction and general information about the study and answered a short background questionnaire. The participants were informed that they could terminate the experiments at any time without explanation or consequences and they gave written informed consent to participate in the study. The experimental procedure was in accordance with the Declaration of Helsinki and the study was approved by the Swedish Ethical Review Authority (Dnr 2024-00861-01).

Before conducting the real experiments, each participant pair underwent a block of test interactions to familiarize with the task and the setup. The drivers were instructed to drive around in the virtual world and that they might encounter pedestrians with crossing intention. They were told that they were free to decide how to behave in an interaction with a pedestrian and that it was their decision whether to yield. The pedestrians were asked to stand on the curb and that they wanted to get to the other side of the road. Thereby, we explicitly set their overarching behavior intent to "cross". The intentions of the non-reactive pedestrians agents was set to "not cross" and the respective motion data was not provided to the system. The pedestrians were instructed to wait with their crossing decision until rain started falling. This was their cue to make a crossing decision and to cross when they thought it was appropriate to do. The reason to select rainfall as the cue to make their crossing decision was that we were aiming for a continuous signal that did not distract them from the original task, and that did not directly tell the participant to cross, rather prompt them to consider crossing. The rainfall was activated when the approaching vehicle reached a distance of 65 m to the pedestrian. The participants, both drivers and pedestrians, were explicitly asked to behave as natural as possible and act as they would in the real world. The participants received no further instructions regarding their behavior or decision making. Prior to the experiments with cHMI activated, the participants were shown images of the HMI that could be displayed to them in their respective role. Between the test blocks, the participants were asked to fill out questionnaires stating whether they had seen any HMI and evaluating their experience with the system. After being teleported to the next interaction, pedestrians were allowed to move freely. Some participants executed crossing actions between two consecutive trials before the decision making cue of the next interaction had been triggered. To obtain comparable and consistent data, we removed an interaction from the final dataset if a pedestrian was already crossing when the cue was triggered, or if the pedestrian completed a preceding crossing maneuver within the 2 s before the cue. In total, 34 interactions were removed due to premature crossing. Prior to the study, we conducted preliminary tests and adjusted the size of the symbols such that they were perceivable and distinguishable. Thereby, we guaranteed general visibility of the eHMI, also at distances around 60 m. After the experiments, the participants were asked to fill out a questionnaire answering the questions how difficult it was to perceive and interpret the respective signals. Table 7 in Appendix A presents the results of this questionnaire, indicating overall good visibility and understandability of the messages.

2.5 Cooperative behavior planning

In interactions, traffic participants need to negotiate the passing order. However, if every agent plans their own behavior regardless of the behavior of the other traffic participants, critical or inefficient situations can occur. Hence, estimating the other one's intention and predicting their behavior is equally important as planning the own next actions. Successful resolutions require cooperative behavior, i.e., interaction partners need to account for each other's benefit and costs.

In this study, we used a cooperative behavior planning framework, that has been developed for automated driving (AD). The system has been tested and evaluated in simulation and in real prototypes, enabling real-time operation at a planning frequency of 4 Hz (Amann et al., 2024; Probst et al., 2021; Wenzel et al., 2025, 2021). We used the cooperative behavior planner to create behavior recommendations and select the signals communicated by the cHMI, but not for actual vehicle control. In each planning step, the behavior planning system processed relevant information, including the ego vehicle's state (position, velocity, acceleration), state information about other traffic participants, and map data, such as the center of the vehicle lane. The system performed a full planning step to obtain a target vehicle trajectory, which, in principle, could be actuated by an AV. In each planning cycle, the system identified potential cooperation partners, particularly those involved in imminent interactions, such as a pedestrian with crossing intent. If there was a relevant cooperation partner, the system planned behavior for multiple potential outcomes. In practice, the two desirable outcomes were "vehicle passing first/cooperation partner passing second" or "cooperation partner passing first/vehicle passing second". Each potential outcome included an interaction-aware trajectory prediction for the interaction partner, i.e., assuming the pedestrian could either intend to cross first, or stay on

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the side walk waiting for the vehicle to pass. The system ensured that the biased prediction remained plausible (see Wenzel et al. (2025) for details). For each prediction, the system created multiple planned vehicle trajectories, optimizing collision risk, driving comfort, and utility. The optimization objective also contained utility and comfort terms for the cooperation partner (pedestrian), i.e., it considered the interest of both partners. The system also took into account that frequent switching between the different outcomes should be avoided. Subsequently, it selected the best plan across all outcomes. The preferred outcome implied optimal joint costs accounting for the interests of both agents in a given situation at the current time. Finally, the planning system returned information about the recommended behavior and the best alternative to the cHMI. The best alternative referred to the best combination of planned vehicle behavior and predicted pedestrian intention that leads to a resolution other than the recommended resolution (Amann et al., 2024). The output contained the full trajectories as well as high-level semantic information (e.g., who crosses first) and reasoning information about the overall situation (e.g., if the vehicle behavior for all potential outcomes is the same).

2.6 Cooperative HMI (cHMI)

We developed an ADAS, the cooperative HMI (cHMI), which communicated recommended behavior options to the driver and outside pedestrians to coordinate their actions and facilitate cooperative resolutions. We adapted the AD behavior planner to the setting with a human driver. The cHMI extends the AD behavior planner by a tracking module that compared the observed with the recommended behavior. This allowed for recommendations based on the interaction partners' behaviors. A recommendation refers to the preferred outcome that the cooperative behavior planner identified and planned for as the best resolution for both participants, i.e., "Pedestrian first" or "Vehicle first". In general, a successful cooperative resolution was achieved if a situation was resolved in accordance with this recommendation. Due to the dynamic and ambiguous nature of traffic interactions, it was possible that the desired outcome changed during an interaction, which could also cause the recommendation to switch. The cHMI comprised the individual iHMI and eHMI components and the communication signal selection that harmonized internal and external messages, such that the signals were consistent and matched the respective situation.

2.6.1 HMI signal design

As an evaluation of HMI symbol designs was not the focus of this study we did not follow a structured design approach but rather constructed basic messages that were explicitly explained to participants before the experiments. Nevertheless, we tried to take into account some findings of prior work, in particular with respect to eHMI design. The presented design should be understood as a one of many possible approaches to convey the intended messages. For the driver, the iHMI signals translated the recommendation into the required behavior, i.e., "Yielding" or "Driving on", to achieve the desired outcome. The iHMI signals were static symbols showing a pedestrian and a yellow or green colored road, which were visualized on the head-up display of the car. The road was colored in yellow when the driver was recommended to yield to the pedestrian and give right of way. Green was selected when the driver was recommended to drive on. The positioning of the pedestrian pictogram in the iHMI symbols varied, depending on the respective side of the road where the real pedestrian was detected, conveying information about the pedestrian's position relative to the vehicle. Studies have found that eHMIs should rather inform external road users about the vehicle behavior or its intention than advising the interaction partner to behave in a certain way (Eisele et al., 2024; Lee and Daimon, 2025). Hence, the eHMI symbols were designed as an explicit representation of the driver behavior, which was in line with the recommendation. Two types of symbols were used for the eHMI. White or amber colored chevrons indicated the vehicle's intention. White was selected when the vehicle was yielding and amber was selected when the car intended to drive on. The external signals were partially dynamic. The chevrons were animated and moved downward when the driver was giving right of way, emphasizing the pitch motion of the vehicle. They moved upward when the driver was not stopping. Chang et al. (2017) reported promising results of external cues replacing eye contact between pedestrians and human drivers. Thus, in addition to the chevrons, the pictogram of an eye was displayed on the eHMI when the vehicle was yielding, indicating that the driver had seen the pedestrian and was yielding to let them pass. The eHMI symbols appeared on one of the two external displays mounted below the front lights of the car. The message was activated on the display that matched the side of the pedestrian with respect to the oncoming car. The eHMI switched from "Yielding" to "Stopping" when the vehicle speed dropped below 0.5 m/s. The possible symbols and their respective interpretations are shown in Table 1. An HMI activation referred to the individual activation of a symbol on the internal or external display.

2.6.2 Driver behavior tracking

The internal tracking module detected and tracked driver behavior. Based on the vehicle speed and acceleration, driver behavior was classified as *yielding*, *cruising*, or *accelerating*. Acceleration strength and the duration of a behavior influenced the classification: The longer a certain behavior remained, the more likely it would have been selected as the intended behavior in the current tracking step. Changes caused by strong acceleration values led to faster adaptation of the estimated driver behavior. After estimating the driver behavior, incorporating the current state and previous driver behavior, the tracking module matched this behavior with the recommended behavior to determine whether the driver behavior complied with the recommendation. If the cHMI recommended "Yielding", the estimated driver behavior was required to be classified as yielding as well, and the current vehicle acceleration was not allowed to exceed the required mean vehicle acceleration within the first

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Table 1: Possible iHMI and eHMI signals and interpretation. The respective interpretation (iHMI or eHMI) was explained to the participants (driver or pedestrian) before starting the experiments with the cHMI.

Yielding (iHMI)	**Driving on (iHMI)**
	
There is a pedestrian who wants to cross the street. The car recommends you let the pedestrian cross first.	There is a pedestrian who shows no intent to cross the street. The car recommends you continue driving.

Yielding (eHMI)	**Stopping (eHMI)**	**Driving on (eHMI)**
		
The car has observed you and is yielding to let you pass.	The car observed you and stopped to let you over.	Watch out, the car is not stopping for you.

4 s of the recommended trajectory by more than 0.5 m/s^2 to be considered as compliant. Compliant driver behavior was also detected if the driver was cruising (absolute acceleration < 0.25 m/s^2) or accelerating (acceleration ≥ 0.25 m/s^2) while the recommendation was "Driving on".

2.6.3 Activation logic

The activation of the cHMI and the respective message shown to the driver depended on the behavior compliance and the current recommendation. Figure 3 shows a visualization of the cHMI activation logic. Two exemplary situations demonstrating the functionality of the cHMI are explained and discussed in Appendix B. If the driver did not comply with the recommendation, the iHMI was activated and the driver got informed about the cooperation opportunity by the respective signal according to the recommendation. If the driver behavior matched the recommendation, no message was shown on the iHMI since the driver already behaved correctly and there was no need for intervention by the system. After an iHMI message has been shown, there were several possibilities for how the driver could react to the signal. If the driver reacted by adapting their behavior according to the recommendation, the iHMI was deactivated since the driver exhibited the expected behavior. A correct behavior adaptation within an assumed reaction time of 1.5 s after an iHMI "Yielding" message was interpreted as a deliberate driver reaction in accordance with the recommended behavior. Huang and Pitts (2022) found typical driver response times between 1 s to 2.5 s following takeover requests. This reaction suppressed further iHMI signals that recommend "Driving on", as the driver already confirmed the first message and approved their yielding intention. If a driver, however, kept accelerating until the assumed reaction time elapsed, or actively switched their behavior to accelerating, this reaction was interpreted as a driver override. This means that the driver deliberately expressed their disagreement with the recommended "Yielding" behavior. In order to prevent communicating undesired recommendations, no further "Yielding" signals were shown in that case. After a driver override was detected, the system was reset if the driver behavior matched the underlying behavior recommendation — either if the driver changed behavior switching to yielding, or if the recommendation by the behavior planner switched to "Driving on". If a driver continued cruising, ignoring the initial message by not changing their behavior (neither approving the recommendation nor overriding), the cHMI continued showing its message.

As long as the driver did not exhibit the expected behavior, an external signal was considered unsafe. Hence, the eHMI could only be activated once the driver behavior was in accordance with the recommendation. To avoid unnecessary eHMI

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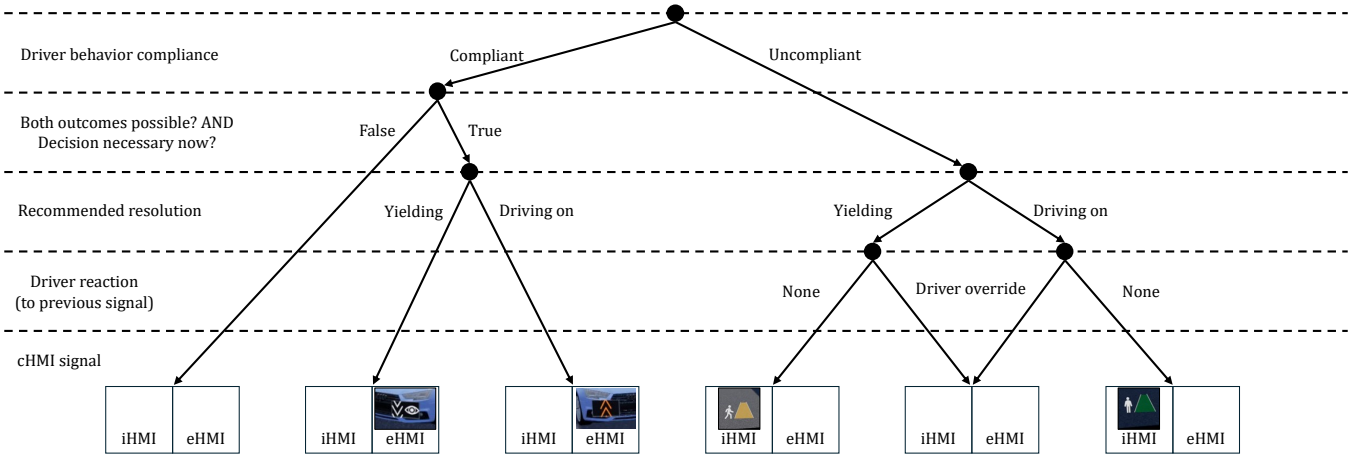

Figure 3: Detailed scheme of the cHMI activation logic.

signaling and reduce cognitive load for external road users, additional semantic criteria that verify the need for behavior coordination were required to be fulfilled for eHMI activation. Those criteria included that both outcomes (i.e., "Pedestrian first" and "Vehicle first") were realistic possibilities how the situation could resolve. E.g., if a pedestrian was close to crossing the vehicle's path because they already stepped onto the road, the outcome "Vehicle first" could have become unrealistic, thus, being no longer taken into consideration by the behavior planner. Similarly, if it was unfeasible for the vehicle to stop to let the pedestrian cross, the situation was considered out of scope of cooperation and the outcome "Pedestrian first" was no longer considered as a realistic resolution. Hence, the pedestrian reaction was implicitly reflected in the signal selection of the cHMI. Additionally, the vehicle behavior for the two respective outcomes had to be sufficiently different, such that the vehicle had to make a decision for either option (for details see Amann et al. (2024)). Once the eHMI communicated the vehicle behavior in an interaction, it was kept active, signaling in line with the recommendation to achieve a consistent and continuous information transfer to the pedestrian.

2.7 Measures

We used a set of subjective and objective measures and different test methods to evaluate the effect of the cHMI on vehicle-pedestrian interactions. We used the Short User Experience Questionnaire (UEQ-S) (Schrepp et al., 2017) and System Usability Scale (SUS) (Lewis, 2018) to measure the subjective assessment of the cHMI and its usability[1].

The start of an interaction was defined as the moment when the vehicle passed the 65 m threshold since this triggered the cue for the pedestrian decision making, and it activated the cHMI. As discussed, the scenario was designed that a successful cooperative resolution initially implied that the pedestrian crossed the road before the vehicle passed. Interactions with this outcome were denoted as "Pedestrian first". Interactions with the pedestrian crossing after the vehicle were referred to as "Vehicle first". We compared the number of "Pedestrian first" interactions in the two conditions to analyze the influence of the cHMI on the proportion of cooperative resolutions.

The crossing initiation delay (CID) is a commonly used metric to evaluate a pedestrian's decision making (Dietrich et al., 2020; Eisele et al., 2024; Lee et al., 2025; Wilbrink et al., 2021). We defined the CID as the time delay between the interaction start and the crossing initiation of the pedestrian. The crossing initiation was defined as the moment at which the pedestrian distance to the middle of the road fell below a threshold of 2 m while the absolute walking speed exceeded 0.4 m/s. The joint resolution time (JRT) denoted the time delay between the start of an interaction and the moment at which the second agent passed the interaction point at which the paths of the vehicle and pedestrian intersected. The JRT represented the joint costs of both agents during the interaction.

We used the number of braking events to evaluate the influence of the cHMI on driver yielding decisions. A braking event was defined as the moment at which a driver applied a force > 1 N on the braking pedal. Moreover, we evaluated the time-to-brake (TTB), which denoted the time from the start of the interaction until the first braking event. The vehicle acceleration was used as a measure to evaluate the individual discomfort for the driver when yielding to the pedestrian. As indicated by Tian et al. (2023), the change rate of the TTC, denoted as $\dot{\tau}$, plays an important role in a pedestrian's perception of vehicle deceleration. We used $\dot{\tau}$ as measure to evaluate the implicit communication that could be perceived by the pedestrian.

Additionally, we used custom metrics to evaluate the participants' reaction to the respective HMI and assessed the overall system compliance and effectiveness. The cHMI communicated cooperation opportunities, recommending the driver either to yield to the pedestrian or to drive on. After a signal that communicated a "Yielding" recommendation, a driver reaction was considered to be in line with the recommendation if the driver reduced the velocity within an assumed reaction time after the iHMI signal. If the system recommended "Driving on" and passing before the pedestrian, the behavior was classified as in line

[1]We used the Swedish versions of both questionnaires. SUS has only been evaluated for drivers.

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if the driver reacted by keeping constant velocity or accelerating within the reaction time. On the external side, a pedestrian reaction was considered to be in line with an eHMI "Yielding" signal if the pedestrian initiated their crossing within the reaction time after the eHMI signal. Pedestrian behavior in reaction to communicating that the driver is "Driving on" was classified as in line with the recommendation, if the pedestrian initiated their crossing earliest when the vehicle has passed. This definition allowed evaluating an agent's immediate behavior in reaction to a communicated message. We analyzed the compliance for different reaction times. We also measured the effectiveness of the cHMI. As discussed above, in a single interaction it was possible that multiple signals were communicated. The messages could repeatedly communicate the same underlying recommendation, or they could indicate a switched recommendation. To evaluate the effectiveness, we focused on the individual recommendations that were given in each interaction. By design, when the cHMI communicated the driver's intention to the pedestrian through the eHMI, the driver behavior was in line with the recommended behavior. In contrast, as long as the driver did not behave as expected, the eHMI could not be activated, thus, the pedestrian could not be directly influenced by the cHMI. Only if the eHMI was activated, the cHMI could influence the behavior of both participants. Hence, we counted unique recommendations when the eHMI was activated, indicating influence of the cHMI on both agents. Such recommendation was classified as compliant if the interaction was resolved according to the respective outcome. Conversely, a recommendation was considered as uncompliant if the final outcome did not match this recommendation. We measured cHMI effectiveness as the share of compliant recommendations among all unique recommendations that had an eHMI activation.

For categorical data, such as the number of "Pedestrian first" interactions or the number of braking events, Generalized Linear Mixed Models (GLMMs) were fitted to examine the effect of the cHMI comparing the two experimental conditions. For continuous data, such as CID, JRT, or vehicle acceleration, we used Linear Mixed Models (LMMs)[2]. These models were suitable for the dataset due to their applicability for within-between-subject studies. Linear models can handle dependent data and multiple observations, and they are robust regarding unbalanced data, which was a result of the data post-processing and removing invalid interactions. They allowed for random effect modeling across the different subjects, i.e., participant pairs. Each participant pair contributed multiple interactions and we assumed that these data were not independent. Random effects were specified with a random intercept for each participant pair. Modeling a random intercept allowed considering varying baseline behavior for each participant pair. If the number of samples in each group was sufficiently large, a random slope for the experimental condition was additionally included in the random effects model. With the random slope, we assumed that each group responded differently to the cHMI. Fixed effects were modeled using the experimental condition or the passing order. Note that the parameters of the GLMMs are denoted in log-odds scale, except for the odds-ratio (OR).

We used χ^2-tests for two specific categorical analyses. We conducted an exact McNemar test to check for a symmetrical effect of the system on the individual participant pairs. Moreover, we used a χ^2-contingency-test to test for similarity in the number of braking events between the full dataset and the subset containing only those experiments that were resolved with "Pedestrian first".

3 Results

Due to technical issues, 2 driver-pedestrian pairs conducted 9 interactions and for 4 pairs 7 interactions were recorded. Overall, data from 558 interactions was recorded. All recorded experiments were successfully finished with both participants passing through the interaction. No collision events were detected and no trials had to be aborted due to motion sickness. As part of data post-processing, interactions in which the pedestrian was crossing right before the decision cue, i.e., start of the rain, were removed from the dataset (see Section 2.4). After cleaning the data accordingly, 524 out of 558 interactions remained, resulting in a share of 93.91 % valid interactions, of which 258 were conducted in the baseline condition without the cHMI and 266 interactions were conducted with the cHMI being available. The group size of valid interactions for each participant pair across both conditions that remained after post-processing varied between 6 and 17 interactions. The cHMI communicated behavior options to either driver, pedestrian, or to both participants in 260 of 266 interactions. These interactions could be separated into 192 interactions in which the driver behavior initially was not in line with the recommendation, hence, triggering an iHMI activation at the start of the interaction. In 68 interactions, the initial driver behavior was in line with the recommendation, thus suppressing an iHMI activation, out of which 18 interactions were finished without any iHMI activation due to the driver's behavior compliance during the whole interaction. In total, 275 iHMI messages were activated. The eHMI was activated in 217 interactions and a total of 329 eHMI messages were shown.

According to the study design, the desired outcome of the interactions was "Pedestrian first" initially, which is why this type of resolutions was considered to evaluate the effect of the cHMI cooperative resolution. As illustrated in Figure 4 (left plot), 46.51 % of interactions in the baseline condition were resolved with pedestrian crossing before the vehicle. This share of cooperative resolutions increased to 77.07 % out of 266 interactions in the cHMI condition. A GLMM with experimental condition as fixed effect and a random intercept for each participant pair and random slope estimation for the effect of experimental condition on each participant pair was fitted to evaluate the effect of the cHMI on the outcome of a situation ($N = 524$, Intercept $= -0.242$, $\beta = 2.208$, $SD = 0.195$, $z = 11.339$, $OR = 9.101$, $p < .001$, 95% $CrI = [1.827, 2.59]$). The random effects model indicated that the subjects differed both in the baseline behavior ($SD = 2.092$ in log-scale) as well as the cHMI effect ($SD = 0.824$ in log-scale). In the condition with cHMI, 272 iHMI messages communicating a "Yielding" recommendation were activated, and 3 messages recommending "Driving on" were shown. On the external display, 296

[2]The LMMs and GLMMs were fitted using the `MixedLM` and `BinomialBayesMixedGLM` functions from the `statsmodels` library with Restricted Maximum Likelihood (REML) and Broyden–Fletcher–Goldfarb–Shanno (BFGS), respectively (Seabold and Perktold, 2010).

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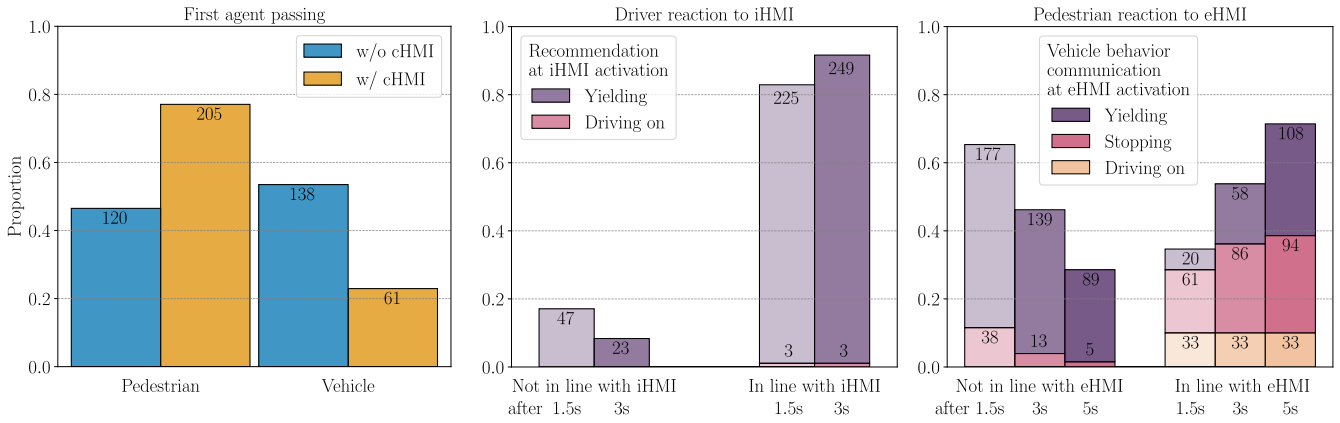

Figure 4: Proportion and absolute numbers of situations resolved by pedestrian/vehicle crossing first (left). Driver (middle) and pedestrian (right) behavior reaction alignment with respective HMI message for each individual signal. A behavior reaction was classified as in line with the respective HMI if the addressed agent reacted with the expected behavior within a reaction time of $\{1.5, 3, 5\}$ s after the HMI activation.

messages occurred communicating the driver's intention to give right of way (197 "Yielding", 99 "Stopping") and 33 signals indicated "Driving on". The middle plot of Figure 4 shows that 1.5 s after the iHMI activation, 82.91 % of all iHMI signals were followed by an immediate driver reaction which was in line with the recommended behavior. The share of compliant driver reactions increased to 91.64 % after an assumed reaction time of 3 s. Pedestrians exhibited the expected reaction within the first 1.5 s after an eHMI activation in 34.65 % of all cases. This share increased to 53.8 % and 71.43 % after 3 s and 5 s, respectively, as depicted in the right plot of Figure 4. The cHMI achieved an effectiveness of 89.55 %, measured as the share of recommendations matching the final outcome from all unique recommendations that had an eHMI activation.

We used UEQ-S and SUS questionnaires for the subjective evaluation of the cHMI. The cHMI achieved a Pragmatic score of $M = 1.471$ ($SD = 1.342, \alpha = 0.88$), a Hedonic score of $M = 1.35$ ($SD = 1.174, \alpha = 0.87$), resulting in an overall UEQ-S score of $M = 1.411$ ($SD = 1.149$). High α-values (> 0.7) indicate consistent answers across individual subjects. Among drivers, system usability was rated with a SUS of 82.4. Figure 5 visualizes the individual effect of the cHMI for each participant pair. The effect was measured as the change in proportion of "Pedestrian first" resolutions comparing the conditions with and without cHMI. For 23 pairs, the cHMI led to an increased proportion of "Pedestrian first" resolutions compared to the baseline. For 8 pairs, the proportion remained the same in the two conditions. Out of those 8 pairs, 3 pairs finished all interactions with "Vehicle first" in both conditions, and for 4 pairs the pedestrian always crossed first. There was another

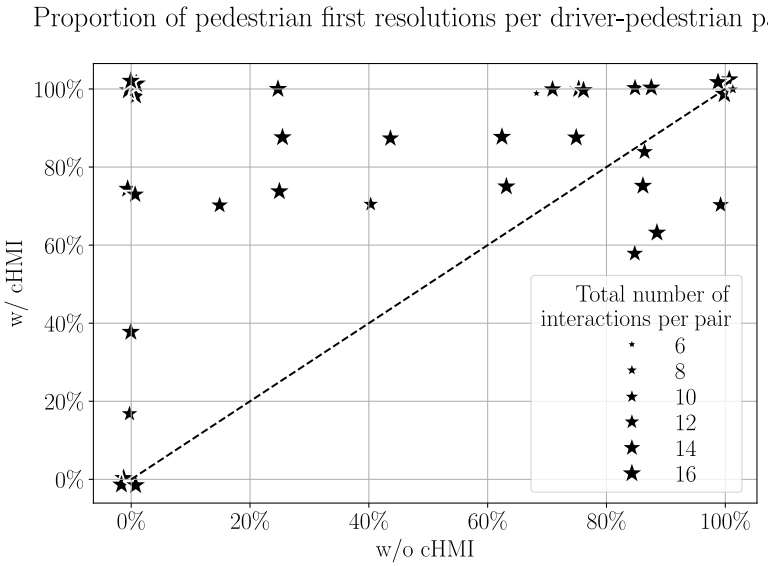

Figure 5: Individual effect of the cHMI per driver-pedestrian pair measured as change in proportion of interactions resolved as "Pedestrian first". The dashed line indicates no change between the two conditions. The marker size relates to the total number of interactions included for each pair.

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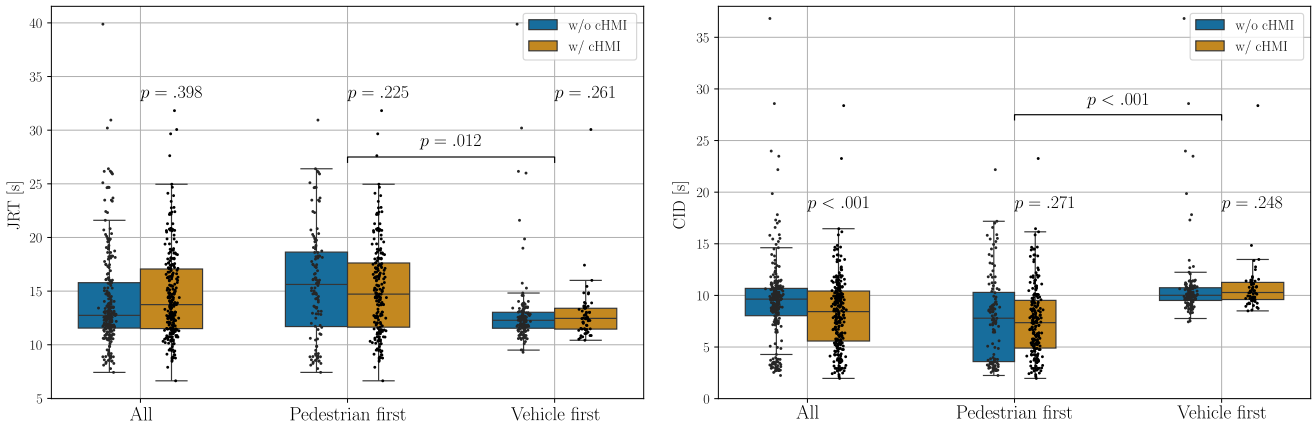

Figure 6: Joint resolution time (JRT) and crossing initiation delay (CID) sorted by experimental conditions for the sets with All interactions, "Pedestrian first" resolutions, "Vehicle first" resolutions.

group of 4 pairs, that exhibited a smaller proportion of "Pedestrian first" resolutions with the cHMI than in the baseline condition. Among pairs that never had the pedestrian crossing first in the baseline condition, 6 pairs could be identified, where the pedestrian crossed first more than 70 % with the cHMI. Under the assumption that the overall "Pedestrian first" ratio of $r_{\text{base}} = 46.51$ % (see Figure 4) for the baseline condition also applied to each individual participant pair, we classified each pair in both conditions regarding the respective "Pedestrian first" proportion relative to r_{base} (crossing more often than $r_{\text{base}} \rightarrow$"Yes"; crossing less often than $r_{\text{base}} \rightarrow$"No"). We conducted an exact McNemar test to test for a symmetrical effect of the cHMI. The base assumption of the McNemar test is that the system's effect is symmetrical, i.e., the number of pairs where the pedestrian crossed first less than r_{base} in the baseline and more than r_{base} with cHMI is the same as the number of pairs where the pedestrian crossed first more than r_{base} in the baseline and less than r_{base} with cHMI. The result of the McNemar test indicated an asymmetric effect of the cHMI on the individual pairs' behavior compared to the baseline ($p < .001$).

Next, we analyzed the influence of the cHMI on JRT and CID. Those measures quantified the benefit for the respective interaction partners representing the cooperativity of an interaction. Figure 6 shows the distribution of JRT (left) and CID (right) by experimental condition for all interactions, experiments resulting in "Pedestrian first", and experiments resulting in "Vehicle first". Table 2 presents the results of the fitted LMMs. The cHMI did not have a notable influence on JRT. However, for the full dataset the CID decreased with cHMI. The right plot in Figure 6 shows that the general effect on CID (decreasing CID) was caused by the larger number of pedestrians crossing before the vehicle with cHMI. Fitting LMMs for the subsets of "Pedestrian first" resolutions and "Vehicle first" resolution individually did not indicate any difference between the two experimental conditions for CID. No significant influence of experimental condition on JRT for either of those subsets could

Table 2: LMM results for JRT and CID

Fixed effect	DV	Group	Random effect	N	Intercept	β	SE	z	p	95% CI
Experimental condition	JRT	All	Intercept + slope	524	14.246	0.408	0.483	0.845	.398	[-0.538, 1.353]
		Pedestrian first	Intercept	325	15.354	−0.350	0.288	−1.214	.225	[-0.914, 0.215]
		Vehicle first	Intercept	199	13.555	−0.399	0.355	−1.123	.261	[-1.096, 0.297]
	CID	All	Intercept + slope	524	9.344	−1.114	0.299	−3.724	< .001	[-1.701, -0.528]
		Pedestrian first	Intercept	325	7.618	−0.295	0.267	−1.102	.271	[-0.819, 0.230]
		Vehicle first	Intercept	199	11.441	−0.401	0.347	−1.155	.248	[-1.082, 0.280]
Passing order	JRT	All	Intercept + slope	524	13.919	0.885	0.354	2.503	.012	[0.192, 1.578]
	CID	All	Intercept + slope	524	11.659	−4.475	0.34	−13.149	< .001	[-5.142, -3.808]

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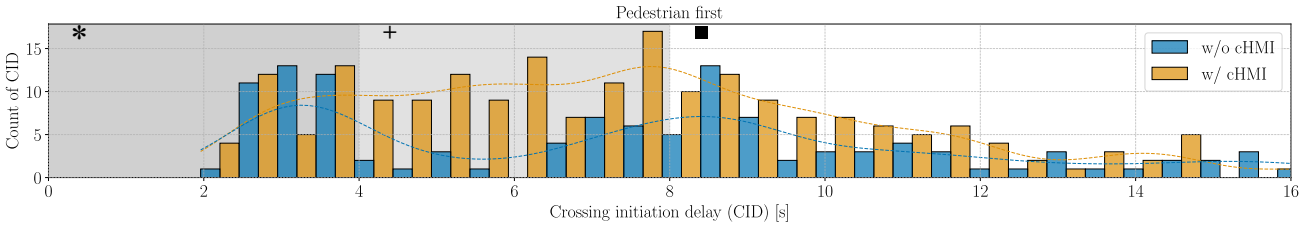

Figure 7: CID sorted by experimental conditions for the set with "Pedestrian first" resolutions. The shaded areas denote the phases of *early* (∗), *intermediate* (+), and *late* (■) crossings. The CID-histogram highlights the bimodality of crossing events in the baseline condition.

be found. Note that reliable random slope estimation was not possible for the subsets because some participant pairs only contributed a single observation (minimum group size = 1) to either of the subsets. We therefore fitted a LMM with random intercept only for "Pedestrian first" and "Vehicle first" subsets. JRT and CID differed regarding the influence of passing order as fixed effect on the respective measure. It should be noted that the passing order was not an independent variable by study design. During the study, the participants were free to decide how to behave and to negotiate the outcome of an interactions. Hence, the subsets considering the passing order individually were an implicit result of the observed behavior.

Figure 7 depicts the histogram of CID, which represents the occurrence of crossing events, for "Pedestrian first" resolutions. The histogram shows the bimodal distribution of crossing events for the baseline condition, which has been found in previous work (Haq et al., 2024; Lee et al., 2025; Tian et al., 2023). We separated the interactions that were resolved with "Pedestrian first" by CID into three phases: *early* ($0 < \text{CID} < 4$ s), *intermediate* ($4\text{ s} \leq \text{CID} < 8$ s) and *late* ($8\text{ s} \leq \text{CID}$). The threshold that separated *early* and *intermediate* crossings could be motivated by the findings of Haq et al. (2024); Tian et al. (2023). They showed that in situations where the vehicle has not yet started decelerating, almost no crossings occurred at TTCs smaller than 4 s. Only if the vehicle started reducing its velocity, pedestrians started crossing again in the second stage accepting the yielding behavior. Hence, this threshold distinguished *early* crossings from *late* crossings. In our scenario, this TTC threshold was reached earliest after a CID of approximately 4 s if the driver took the speed limit into account. The upper threshold separating *intermediate* and *late* phases represented the approximate time that a driver needed from the beginning of an interaction until passing the pedestrian if they drove at constant velocity with 30 km/h (including a small margin). Figure 7 highlights the shift in the distribution of crossing events from the bimodal distribution in the baseline condition to a more even distribution with cHMI. With cHMI, crossing events were more likely to occur in the *intermediate* phase.

3.1 Effect of the cHMI on driver behavior

We evaluated the effect of the cHMI on driver behavior. Considering all interactions, drivers braked more often with cHMI than in the baseline condition, as indicated by a GLMM fitted with experimental condition as fixed effect and random effect modeling including a random intercept for each participant pair and random slope for experimental condition ($N = 524$, Intercept $= -0.847$, $\beta = 2.135$, $SD = 0.172$, $z = 12.449$, $OR = 8.455$, $p < .001$, 95% $CrI = [1.799, 2.471]$). The random effects model indicated between-subject variability in both baseline performance ($SD = 1.923$ in log-scale) and cHMI responsiveness ($SD = 0.657$ in log-scale). Similar to the full dataset, in the "Pedestrian first" situations we obtained more braking events with cHMI ($N = 325$, Intercept $= 1.458$, $\beta = 1.337$, $SD = 0.251$, $z = 5.33$, $OR = 3.8073$, $p < .001$, 95% $CrI = [0.845, 1.828]$). Here, we only included a random intercept due to the group sizes. Table 3 denotes the occurrence of braking events. A χ^2-contingency-test comparing the number of braking events showed a strong similarity between the full dataset and the subset of "Pedestrian first" resolutions ($\chi^2(1, N = 538) = 0.275$, $p = .6$). Figure 8 shows the histograms of TTB, i.e., braking events, and median lineplots of vehicle acceleration separated by experimental condition for the full dataset and the subset of "Pedestrian first" resolutions. We fitted a LMM with experimental condition as fixed effect and random effect modeling including a random intercept to analyze the effect of the cHMI on TTB. Due to the group sizes, we did not include random slopes for the TTB analysis. Considering all interactions, if drivers braked, they braked earlier with the cHMI compared to the baseline condition ($N = 280$, Intercept $= 4.753$, $\beta = -0.848$, $SE = 0.266$, $z = -3.187$, $p = .001$, 95% $CI = [-1.370, -0.327]$). With cHMI, we obtained a lower minimum vehicle acceleration, i.e., stronger braking, compared

Table 3: Contingency table of observed braking events N_{braking} (All vs. Pedestrian first)

	All	Pedestrian first
w/o cHMI	96	82
w/ cHMI	184	176

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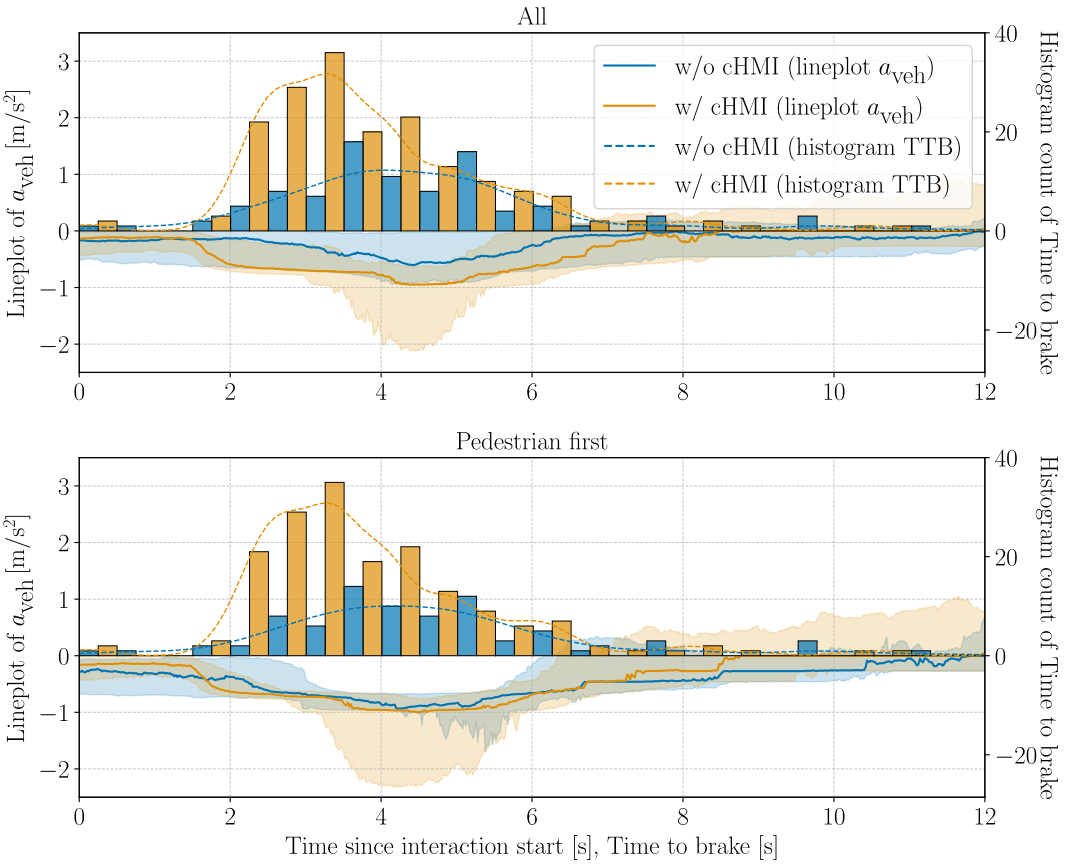

Figure 8: Effect of cHMI on driver behavior: Longitudinal vehicle acceleration (median lineplot incl. 50 % percentile from 25% to 75%) and distribution of TTB, i.e., braking events, for full dataset (top) and interactions resolved with pedestrian crossing before the vehicle (bottom). The left y-axes refer to the vehicle acceleration lineplots over the time since the start of the interaction. The right y-axes refer to the distribution of TTB (histogram + fitted probability density function).

to the baseline ($N = 524$, Intercept $= -1.605$, $\beta = -1.024$, $SE = 0.204$, $z = -5.02$, $p < .001$, 95% $CI = [-1.423, -0.624]$)[3]. Similar to the full dataset, TTB was smaller with cHMI compared to the baseline in "Pedestrian first" situations ($N = 258$, Intercept $= 4.787$, $\beta = -0.918$, $SE = 0.293$, $z = -3.135$, $p = .002$, 95% $CI = [-1.492, -0.344]$). In "Pedestrian first" resolutions, we also found a lower minimum acceleration with cHMI compared to the baseline ($N = 325$, Intercept $= -2.662$, $\beta = -0.511$, $SE = 0.191$, $z = -2.669$, $p = .008$, 95% $CI = [-0.886, -0.136]$), however, the effect was smaller than in the full dataset (-0.511 m/s^2 "Pedestrian first" vs. -1.024 m/s^2 full dataset). As shown in the lineplot of the vehicle acceleration, the data indicated a similar median acceleration between experimental conditions in "Pedestrian first" resolutions.

3.2 Effect of the cHMI on pedestrian behavior

To analyze the effect of the cHMI on pedestrians, we focused on those interactions that were resolved with "Pedestrian first", and analyzed them in the three phases (*early*, *intermediate*, *late*) individually. Tables 4 to 6 report the contingency tables of crossing events occurring in each phase. The contingency tables consider all interactions that were not resolved until the respective threshold, i.e., that could have been resolved in the respective phase. This means that in Table 4 all interactions are considered; Table 5 takes those interactions into account that were not resolved *early*, and Table 6 reflects the remaining interactions that were not resolved *early* or in the *intermediate* phase. Fitting a GLMM indicated a similarity in the absolute number of *early* crossings for both experimental conditions ($N = 524$, Intercept $= -3.136$, $\beta = -0.317$, $SD = 0.233$, $z = -1.361$, $OR = 0.73$, $p = .174$, 95% $CrI = [-0.774, 0.14]$). Compared to the baseline, the cHMI led to more "Pedestrian first" resolutions in the *intermediate* phase ($N = 452$, Intercept $= -3.122$, $\beta = 2.484$, $SD = 0.171$, $z = 14.497$, $OR = 11.99$, $p < .001$, 95% $CrI = [2.148, 2.82]$). The remaining interactions, which were not resolved *early* or in the *intermediate* phase, also resulted more often in "Pedestrian first" with the cHMI compared to the baseline condition ($N = 334$, Intercept $= -1.818$, $\beta = 2.031$, $SD = 0.271$, $z = 7.498$, $OR = 7.623$, $p < .001$, 95% $CrI = [1.5, 2.562]$, with

[3]Since the group sizes for minimum acceleration were sufficiently large (minimum group size = 6), we used random intercepts and random slopes for fitting the LMM.

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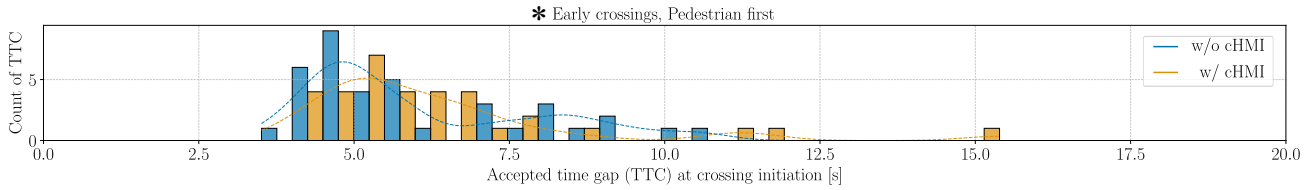

Figure 9: Distribution of accepted TTCs for *early* crossing events (pedestrian crossing first).

random intercept only due to group size). In addition to the absolute numbers of crossing events, we analyzed the distribution of accepted TTC for *early* crossings, which is displayed in Figure 9. We analyzed the accepted TTC for *early* crossings only, since these crossing events represent crossing decisions that were made based on the time gap in the first stage (see Schroeder et al. (2014); Tian et al. (2025)). The mean accepted TTC across both conditions was 6.189 s (median TTC = 5.537 s, $SD = 2.106$ s). As for the absolute number of *early* crossing events, the results indicated a strong correlation between the distributions of accepted TTCs fitting a LMM ($N = 72$, Intercept = 6.604, $\beta = 0.129$, $SE = 0.313$, $z = 0.412$, $p = .68$, 95% $CI = [-0.484, 0.742]$).

Furthermore, we analyzed the influence of the system in situations in which the driver showed weak implicit yielding cues. Less pronounced implicit communication makes it more difficult for a pedestrian to perceive the driver's yielding intention. We classified interactions regarding the strength of the yielding behavior. We considered the minimum vehicle deceleration between the start of an interaction and the crossing initiation of a pedestrian. Yielding cues caused by the vehicle deceleration in this part of the interaction can be interpreted as the strongest implicit cues that could have been perceived by the pedestrian before making a crossing decision. According to the results regarding driver braking, we assumed a threshold of -1.0 m/s^2 (see Figure 8) as the lower threshold for weak yielding. Any scenario, where the minimum deceleration before the crossing initiation was below this threshold was not classified as weak yielding, hence, not considered for this analysis. Similarly, any scenario where the driver did not show any implicit yielding signs before the pedestrian crossed the road or before the driver passed the pedestrian was excluded from this analysis, since the eHMI would not communicate the driver's yielding intention. According to this definition, without the cHMI 111 interactions were classified as weak yielding, of which 34 were resolved with the pedestrian crossing first. With the cHMI, 76 interactions were classified as weak yielding, of which 40 were resolved with pedestrian crossing first. A GLMM with random intercept fitted on the subset of weak yielding situations indicated a difference regarding the outcome between the conditions ($N = 187$, Intercept = -1.796, $\beta = 1.298$, $SD = 0.374$, $z = 3.469$, $OR = 3.662$, $p < .001$, 95% $CrI = [0.565, 2.031]$)

Table 4: Contingency table of *early* resolutions.

	Ped. first *early* res.	*interm.* + *late* res.
w/o cHMI	38	220
w/ cHMI	34	232

Table 5: Contingency table of *interm.* resolutions.

	Ped. first *interm.* res.	Veh. first *interm.* + *late* res.
w/o cHMI	23	197 (= 3 + 194)
w/ cHMI	92	140

Table 6: Contingency table of *late* resolutions.

	Ped. first *late* res.	Veh. first *late* res.
w/o cHMI	59	135
w/ cHMI	79	61

3.3 Trust calibration effect

We conducted analyses regarding trust calibration effects throughout the experiments. The results showed that the effect of the cHMI was independent of the order in which the participants experienced the two conditions (cHMI first vs. baseline first). If participants first did the experiments with the cHMI, the proportion of "Pedestrian first" resolutions was 78.05 %. If they started with the baseline condition, the proportion of "Pedestrian first" resolutions in the cHMI condition (second test block) was 76.22 %. The proportion of "Pedestrian first" resolutions in the baseline condition varied depending on the order of the experiments. If the participants started with the baseline in the first block, the proportion of "Pedestrian first" resolutions was 26.43 %. If they experienced the cHMI condition first, the proportion of "Pedestrian first" resolutions in the baseline condition (second test block) was 70.34 %. Detailed analyses regarding trust calibration and further learning effects can be found in Appendix D.

4 Discussion

Our simulator setup was able to initiate ambiguous interaction situations between participant drivers and participant pedestrians as shown by a relatively high number of pedestrians crossing first in the baseline condition. Despite complex temporal

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coordination of events, only few interactions had to be discarded due to unwanted behavior. In the post-processing step, we removed 34 of 558 (6.09 %) interactions from the dataset and did not consider them in the evaluation. In those experiments, the pedestrians were crossing shortly before the start of the interaction scenario was triggered which compromised the validity of these scenarios and the comparability with other experiments. 18 of these invalid interactions were clustered among two specific participants (10 and 8 interactions, respectively). We want to emphasize that we could not find a direct link to the rainfall as cue for their decision making. Since they all crossed before the trigger, we cannot argue that the rain initiated any unexpected behavior since the rain had not started yet and the cHMI was not activated before their crossing initiation in these cases. This rather indicates that these participants might have had issues understanding the instructions in general. Since we allowed the pedestrians to move freely, they might have observed the car and made a crossing decision before the actual interaction had started. Regarding the effect of the removed data on the distribution of crossing events, we argue that these scenarios would have been counted as *early* resolutions since the crossing event was initiated even before the experiment started. The data of the removed experiments did not show a bias towards either of the two conditions (20 in baseline, 14 with cHMI). Also, for the two specific participants, the removed interactions were distributed nearly equally among the conditions (5:5 and 5:3 for baseline:cHMI). Thus, the invalid data was strongly clustered among two specific subjects, and filtering the data in the described way artificially reduced the share of *early* resolutions among the overall data without having a pronounced effect on one particular condition. Moreover, we did not see any crashes or critical situations during the experiments regardless of the experimental condition. We implemented a safety measure by enabling eHMI activations only if the driver behavior was in line with the recommended behavior, which was handled by the cHMI. The data showed that the cHMI was activated in almost all valid runs. Despite only being triggered when the driver was following the system recommendation, we could see a high number of eHMI activations. The difference in numbers of eHMI activations compared to iHMI activations resulted from the dependency of the eHMI activation on driver behavior as well as the fact that external messages communicating "Yielding" and messages communicating "Stopping" were counted individually.

The traffic scenario was designed such that a cooperative solution implied that the drivers gave right of way to the pedestrian, yet, the drivers were still free to decide what to do and whether to follow the recommended behavior. The compliance and effectiveness analyses showed that most interactions were resolved according to the recommendation indicating a high overall effectiveness of the cHMI, although many pedestrians needed longer than expected to react after an eHMI message. The results showed that drivers usually followed the iHMI and reacted according to the recommendation. For the large majority of all iHMI activations, the driver behavior was in alignment with the recommendation and the driver reacted shortly after the iHMI. In combination with the finding that in the baseline condition only 46.51 % of situations resolved according to the potentially recommended resolution, this result emphasizes the potential of such ADAS to enhance cooperativity in traffic. Pedestrians also acted according to the recommendation of the eHMI in most cases. However, this sometimes required significant time after activation of the signal, such that they were likely also extensively exposed to braking cues by the driver. When displaying a "Stopping" message, the vehicle speed was much lower compared to a "Yielding" message. In line with the findings of Bellet et al. (2022); Dey et al. (2021); Lyu et al. (2025); Serrano et al. (2025), our findings suggest that pedestrians still mostly focused on the vehicle behavior. The results indicated that the vehicles' implicit communication was paramount for the pedestrians' crossing decision, thus they did not blindly trust the eHMI. However, in situations in which the driver exhibited only weak yielding cues making it more difficult for the pedestrian to perceive the vehicle yielding, the results showed a strong effect of the cHMI. Compared to the baseline, significantly more pedestrians crossed first with the cHMI. This effect could possibly be attributed to the eHMI and interpreted as the additional external communication amplifying the driver's yielding intention. These results provide interesting insights regarding the decision making of pedestrians and evidence for the potential of eHMIs. The vehicle behavior was important for the pedestrians' crossing decision, however, an additional explicit signal that emphasized the vehicle behavior could help to understand the driver's intention, especially in situations where the implicit communication was only subtle.

At the same time, the cHMI achieved positive subjective ratings. According to Schrepp et al. (2017), UEQ-S ratings > 0.8 represent positive evaluations. Hence, the UEQ-S scores, evaluating the user experience of the cHMI, could be interpreted as "Good". Moreover, regarding the system usability from the perspective of drivers, the cHMI achieved a result which corresponds to an "A"-grade rating, and which lies within the top 5 %–10 % of comparable SUS ratings (Lewis, 2018). We conclude that the system was well received and was accepted both by drivers and pedestrians. The analysis of the subjective data emphasized that the system was perceived as useful and the larger share of interactions resolved with "Pedestrian first" was appreciated by both pedestrians and drivers.

The cHMI led to a significant increase of cooperative resolutions resulting in "Pedestrian first", whereas in the baseline condition the majority of drivers insisted on their right of way. Large variances in the participants' baseline behavior as well as the effect strength of the cHMI between the subjects showed how differently individual participant pairs reacted. Nevertheless, a strong general effect of the cHMI on the outcome of the situations could be observed. The results of the GLMM's random effects model were in line with the results of the exact McNemar test. The test showed an increase of cooperative resolutions across the majority of participant pairs. The system caused a decrease in cooperative resolutions in only 4 participant pairs, however, these pairs could be identified as participants, where most interactions (in both conditions) were resolved as "Pedestrian first" and the decline of cooperative resolutions could also be due to noise in the behavior.

Besides the effect on the outcome of an interaction, we also investigated the quantitative influence of the cHMI on the costs for a joint cooperative resolution for the interaction partners. We did not find a significant influence of the cHMI on the JRT, the time that it took the second interaction partner to pass through the interaction. Although not statistically significant, the results suggest a tendency towards slightly increasing the JRT with the cHMI. This effect could be explained by the finding

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that the resolution "Pedestrian first" took intrinsically longer compared to "Vehicle first". We interpret this such that, in terms of time, the driver had to pay a similar amount of costs as the pedestrian would benefit from crossing first. Thus, the cHMI contributed to a general willingness to behave cooperatively and give right of way to pedestrians in certain situations. Hence, we conclude that a certain level of disadvantage for the driver was acceptable and reasonable in order to create a joint benefit by letting the pedestrian cross first. We found that the cHMI contributed to a significantly lower CID. With cHMI, pedestrians initiated their crossing on average 1.114 s earlier. Results indicate that this effect was mostly caused by the main effect of more "Pedestrian first" resolutions with the system. Due to the semantic differences between "Pedestrian first" and "Vehicle first" resolutions, we found that the CID differed significantly comparing these two outcomes. However, we did not obtain a significant influence of the cHMI on the CID if looking at either of those subsets individually. Hence, the overall effect of the cHMI on CID was caused by the fact that with the system more drivers yielded to pedestrians allowing more "Pedestrian first" resolutions. The cHMI primarily promoted more cooperative resolutions, in which the pedestrian crossed before the vehicle, rather than improving temporal decision metrics. When looking at three groups of pedestrian crossings according to the CID, results showed that the cHMI did not affect *early* crossings. We found a strong similarity between the two conditions, both regarding the number of crossings as well as for the distributions of accepted TTCs, underlining the independence of *early* crossing decisions of the cHMI. The majority of *early* crossings happened at TTC between 4–7 s, which was in line with previous studies that research pedestrian gap acceptance (Haq et al., 2024; Tian et al., 2023; Wang et al., 2010).

Analyzing the braking behavior revealed a strong correlation between driver braking events in the full dataset and braking events in the "Pedestrian first" subset, indicating a correlation between driver braking and pedestrians crossing first in general. This finding was independent of the experimental condition and it showed that nearly all cases in which the driver braked at some point during the interaction were resolved with "Pedestrian first". However, we found various significant effects of the cHMI on driver braking behavior. With the system, significantly more drivers braked, which suggests that the cHMI increased the willingness of drivers to yield and give right of way to the pedestrian. With the cHMI, drivers started braking significantly earlier with an average effect of -0.848 s compared to the baseline condition. Furthermore, the cHMI influenced the way how drivers braked by means of the minimum acceleration during an interaction. The results showed that the effect of the cHMI on the minimum acceleration was on average -0.511 m/s^2 if we considered the braking behavior in "Pedestrian first" resolutions. From the pedestrian perspective, stronger braking means higher $\dot{\tau}$, which indicates stronger implicit yielding communication from the driver. We also analyzed the pedestrian behavior in relation to the implicit communication that the pedestrians perceived from the vehicle by means of $\dot{\tau}$ (see Appendix C). Separated by the three phases, we observed that the later an interaction was resolved by "Pedestrian first" the more $\dot{\tau}$ increased before the crossing event. For a detailed discussion see Appendix C.

Since the participants conducted multiple runs under similar conditions, we also evaluated possible learning effects of participants throughout the experiments. Detailed results and discussion can be found in Appendix D. With respect to the order of conditions, we could see that participant pairs who experienced the condition with cHMI first showed an increase in "Pedestrian first" resolutions in the baseline condition compared to those who started with the baseline. We did not find a similar ordering effect for the cHMI. Receiving cHMI signals in early interactions might have made participants generally more aware of the cooperative situation possibilities in later experiments. However, due to the balanced ordering of our experiments, this effect does not confound our main findings, but rather leads to an underestimation of the true cHMI effect. We further investigated potential effects of trust calibration of participants with respect to each other (in particular towards the driver) and towards the cHMI (Kraus et al., 2020). Pedestrians might have learned that crossing is safe through repeated exposures to an eHMI "Yielding" signal. We indeed found a slight increase in pedestrian crossings with an increasing number of eHMI interactions (see Figure 11 in Appendix D). However, even at their first exposure to such signal, we could observe about 72% of participants acting in line with the recommended resolution. In addition, when analyzing crossing numbers relative to the overall number of interactions (or also number of interactions in one of the two conditions) of a given participant, we found a very similar tendency of increase. This could point to a more general explanation of pedestrians getting used to a vehicle's yielding behavior or of a trust calibration towards the driver (and their implicit communication cues). However, as the effects could be found consistently across our conditions, they do not confound our main findings of increased cooperation through the cHMI.

5 Limitations

In this research, we investigated traffic situations between two participants interacting with each other as driver and pedestrian. Such experiments, in which both participants can act freely and decide how to behave, are complex and can evolve in various ways. To maximize comparability among the individual interactions and reduce the influence of other possibly confounding factors, we focused on interactions in one type of traffic situations. The scenario was selected such that, despite its simplicity, the situation entailed a high level of ambiguity and the outcome was unclear in the beginning of an interaction. However, the lack of variety might constrain the representativeness for other types or more complex traffic situations. A limitation of this study is that participants, especially drivers, could have behaved particularly compliant, whether intentionally or unconsciously, because they knew they were being observed during the study (Orne, 1962). The study design implied repeated interactions under similar conditions, including the same scenario setting and the same interaction partner. Thus, participants might have learned certain patterns and adjusted their behavior accordingly. We conducted thorough analysis of such learning

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effects and discussed their implications for the study results. Nevertheless, the presented results should be interpreted carefully and should be considered in the context of the respective situation, regarding generalizability and the extrapolation of the findings to other situations.

The study was conducted in a VR-simulation environment that has been designed to enable realistic interactions between human drivers and pedestrians. Despite behavioral differences between VR-simulation environments and behavior in real-world interactions (Serrano et al., 2025), such VR-setups are often used to study traffic interactions, since they offer a suitable method that allows an immersive experience while maintaining participant safety. Although participant feedback regarding their experience in this setup was overall positive, we can not guarantee that the results stand representative for driver and pedestrian behavior in real-world interactions.

Our study did not aim to investigate the effectiveness of certain HMI symbols but focused on the overall system concept. We used simple symbols and explicitly introduced their meaning to participants. By explaining the respective symbols to the participants prior to the experiments, we introduced a certain bias regarding the interpretation of the messages. However, some pedestrian participants still mentioned difficulties in understanding. Optimizing the HMI symbols could further enhance effectiveness and would also be necessary to enable the system's deployment among fully naive pedestrians in general traffic environments. Although, the cHMI logic handled driver compliance and the eHMI could only be activated if the driver behavior was in line with the recommended behavior, explicitly validating the safety of the system was not part of this study. Hence, misinterpreting the eHMI messages could pose a risk to pedestrians.

Eventually, due to the single-factor study design with two levels (baseline and cHMI condition) and the design of the cHMI activation logic, we could only evaluate the influence of the full cHMI system. We were still able to analyze driver and pedestrian reaction compliance with the respective HMI individually and investigate the influence of the driver behavior on the pedestrian. However, an isolated evaluation of the effects of iHMI and eHMI detached from the full system was not possible due to the study design. Similarly, the study does not allow to draw conclusions regarding the HMI coordination as the main reason for the observed effects. Hence, we cannot exclude that similar results could have been achieved with a system that only uses either of the HMIs components.

6 Conclusion

This study showed that the cHMI contributed to significantly more cooperative resolutions, in which the pedestrian crossed before the vehicle. Our results regarding the crossing decision of pedestrians in early and late phases in the baseline condition (regular interactions without any assistive communication) were consistent with the findings of previous studies, underlining the validity of the study. One of the major contributions of the cHMI lies in fostering pedestrian crossing in the intermediate phase between the first stage, in which the crossing decision was mainly based on the time gap, and the late phase, where pedestrians focused on the vehicle behavior and where the vehicle (nearly) came to a full stop. Our analyses suggest that the eHMI was especially useful in situations with weak implicit yielding cues. Overall, we provided support for research hypothesis H1 that the system increased the number of cooperative situation resolutions.

Regarding hypothesis H2, the study showed that the cHMI was accepted by the participants and perceived as an useful ADAS. The system's signals were largely followed, especially by drivers, who responded to the iHMI messages appropriately within a short period of time. An overall lower compliance rate of pedestrians with the respective HMI compared to drivers led us to the conclusion that the pedestrians were hesitant and sceptical towards the human-driven car. Moreover, larger reaction times for pedestrians to comply with the eHMI led us to the conclusion that the pedestrians mostly watched the car and payed attention to the vehicle behavior. The eHMI was mainly used as a secondary cue. Nevertheless, the overall effectiveness of the cHMI was high and most situations were resolved according to the recommendation, hence we concluded that hypothesis H2 could be confirmed with the additional observation that pedestrians did not exclusively rely on the eHMI and that they needed more time to react to an eHMI signal.

We hypothesized that the cHMI reduces the joint costs of cooperative resolutions, thereby reducing the overall time it takes to resolve the interaction (H3). The study showed that with the cHMI pedestrians crossed significantly earlier compared to the baseline, creating a measurable benefit for pedestrians. However, the JRT did not differ significantly with the cHMI, since one agent had to accept a certain personal disadvantage to enable the benefit for the interaction partner. Hence, we reject hypothesis H3.

Additionally, the findings provided insights regarding driver behavior and their reaction to internal behavior recommendation signals. The cHMI could reinforce or even change the intention of the driver, as well as the timing and the strength of their yielding behavior, if they received timely information about a cooperation opportunity. Regarding pedestrian behavior, our study suggests that the crossing decision is based on different cues in different phases of the interactions, which is in line with the findings of previous studies.

Our study underlines the importance of internal and external communication for coordinated action taking for cooperative resolutions. An ADAS based on the proposed system has the potential to improve vehicle-pedestrian interactions. As the results showed the relevance of implicit communication for pedestrian crossings, future studies could investigate how to enhance driver awareness about the effect of their behavior, and how drivers could be influenced to optimize their actions with respect to implicit communication.

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Declaration of competing interests

The authors Markus Amann, Malte Probst, and Thomas H. Weisswange declare that they are employees of Honda Research Institute GmbH. They are inventors on a pending patent application assigned to Honda Research Institute Europe GmbH related to the research presented in this manuscript. The authors Stina Larsson, Maytheewat Aramrattana, and Anna Sjörs Dahlman are employees of the Swedish National Road and Transport Research Institute. These affiliations and interests have been disclosed and managed in accordance with institutional policies. The other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution

Markus Amann: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – Original Draft, Writing – Review & Editing, Visualization; **Stina Larsson**: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Data curation; **Malte Probst**: Conceptualization, Methodology, Software, Writing – Review & Editing, Supervision, Project administration, Funding acquisition; **Maytheewat Aramrattana**: Methodology, Software, Resources, Data curation; **Miguel Ángel Sotelo**: Conceptualization, Supervision, Project administration, Funding acquisition; **Anna Sjörs Dahlman**: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Supervision, Project administration, Funding acquisition; **Thomas H. Weisswange**: Conceptualization, Methodology, Writing – Original Draft, Writing – Review & Editing, Supervision, Project administration, Funding acquisition

Data availability statement

The participants of this study did not give written consent for their data to be shared publicly, so due to the sensitive nature of the research supporting data is not available.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT-4/5 in order to generate the code basis for complex visualizations. ChatGPT has only been used to build the layout of the graphics. The content of the figures is original and authentic. The data visualized in the graphics has not been uploaded to or modified by ChatGPT or any other AI-tool. ChatGPT has also been used as a translation tool and to improve individual expressions in order to achieve linguistic precision that meets the requirements of a scientific article adequately. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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Appendix A HMI perception and interpretability questionnaire results

Table 7: Descriptive statistics for symbol visibility and interpretability. The participants rated how difficult/easy it was to see and interpret the cHMI symbols on a scale from 1=very difficult to 6=very easy.

Question	Group	N	Mean	SD	Mean SE
How difficult/easy was it to see the symbols?	Pedestrian	35	4.31	1.43	0.24
	Driver	35	5.43	0.92	0.15
How difficult/easy was it to interpret the symbols?	Pedestrian	35	4.71	1.43	0.24
	Driver	35	5.29	0.99	0.17

Appendix B Behavior of the cooperative HMI activation logic

Due to the design choice of only activating the eHMI when the driver behavior was in line with the recommendation, we know that the driver behaved compliantly when the eHMI was activated – whether the iHMI had been active before or not. Moreover, due to the relationship between driver behavior compliance and eHMI activation, it could happen that the eHMI got activated and deactivated multiple times, reflecting the driver's compliance with an updated recommendation after the situation had changed. We found interactions in which the system initially engaged by recommending the driver to yield. The driver rejected the recommendation by accelerating, thus, no corresponding eHMI message was communicated to the pedestrian. As the driver continued driving on, the outcome "Vehicle first" became preferable, i.e., the recommended resolution switched. Since now the driver behavior was in line with the recommendation, the eHMI got activated and communicated the preferred "Vehicle first" resolution, which was in line with the current driver behavior, to the pedestrian. The pedestrian kept waiting until the vehicle had passed and eventually crossed the road after the vehicle. In this example, the system first had to coordinate the interaction with the driver before communicating to the pedestrian. A joint resolution was only possible after the driver behavior had been in alignment with the recommended behavior. Hence, only the single unique eHMI activation communicating that the driver was "Driving on" was counted, and it was counted as compliant. In another example, the driver first received a "Yielding" recommendation and behaved according to the recommendation by reducing the vehicle speed. Subsequently, the eHMI communicated the driver's yielding intention to the pedestrian. After that, the situation could have been resolved according to the joint behavior recommendation. However, for some reason the pedestrian decided not to cross before the vehicle and kept standing. As the interaction progressed, "Vehicle first" became the preferred resolution. The respective recommendation was communicated to the driver through the iHMI and the driver followed the recommendation once again. Since the driver behaved according to the recommended resolution, the "Driving on" behavior was communicated to the pedestrian through the eHMI. The pedestrian eventually crossed the road after the vehicle. In this situation, the cHMI coordinated two semantically different recommendations with both interaction partners, and they had two separate chances to follow the system and successfully resolve the situation. However, the first joint recommendation had not been successful, hence, it was counted as uncompliant. The second engagement was counted as compliant. These two examples illustrate the importance of coordinating the cHMI messages with the behavior of both interaction partners and while moderating the interaction between them.

Appendix C Pedestrian behavior and implicit vehicle communication

In the following, we will discuss the pedestrian behavior in relation to the implicit communication that the pedestrians perceived from the vehicle in the different phases of an interaction. The perceived implicit communication was measured by means of $\dot{\tau}$, which denotes the change rate of the TTC. Figure 10 shows the pedestrian behavior in relation to the vehicle behavior for the two experimental conditions. In the top row, plots a)–d) depict the median of $\dot{\tau}$ over the time to the crossing event for each crossing phase. Plots e)–h) in the bottom row of Figure 10 display the median lineplot of the distance between the vehicle and the pedestrian with respect to the time of the crossing event[4]. Figure 10a) shows that for interactions resolved in the *early* phase, the progression of $\dot{\tau}$ before the crossing initiation was similar in both conditions. Before the crossing event, $\dot{\tau}$ was close to -1, which corresponds to constant vehicle speed. From the moment of the pedestrian's crossing initiation, $\dot{\tau}$ slightly increased before decreasing again and adjusting at $\dot{\tau} = -1$ when the pedestrian reached the other side of the road. As depicted in Figure 10e), the mean distance between vehicle and pedestrian at crossing initiation in *early* crossings was 40.68 m. For *intermediate* crossings, Figure 10b) depicts that for both conditions, the crossing event occurred approximately 3 s after

[4]Note that for the plotting of $\dot{\tau}$ and d in the *intermediate* phase, the three interactions with "Vehicle first" are not included (see Table 5).

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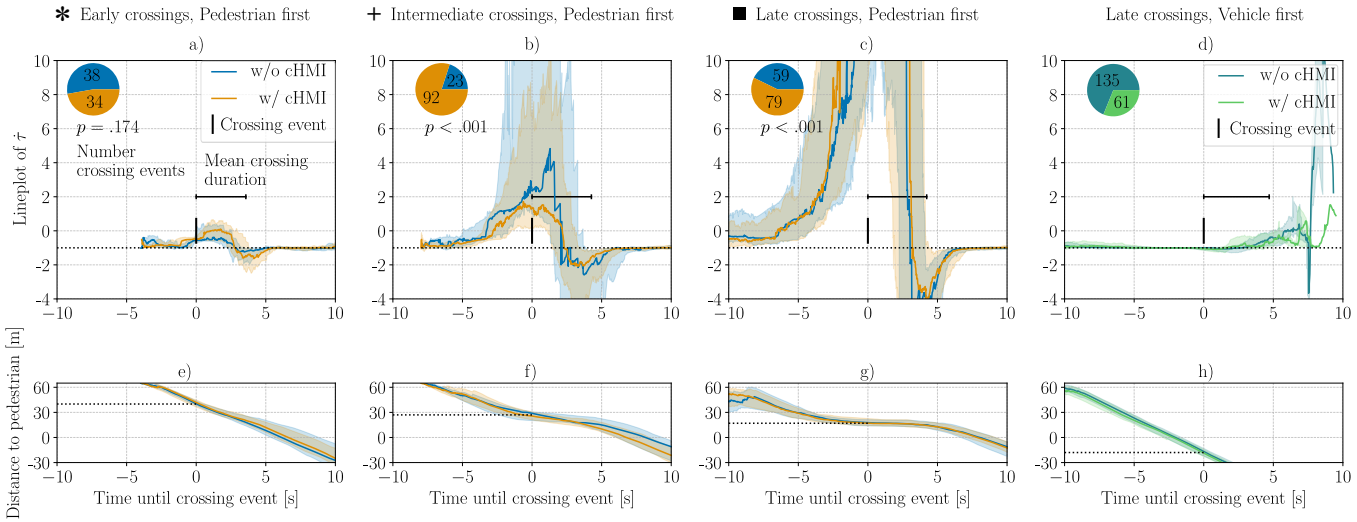

Figure 10: Effect of cHMI on pedestrian behavior: a)–d) Visual cues from pedestrian perspective before crossing event sorted by resolution in different phases of the interaction. The shaded areas around the lineplots visualize the 50 % percentile. The x-axis value of 0 refers to the crossing event. The pie plot in the top left corner of each subplot refers to the absolute number of crossing events across the two conditions in each phase (see Tables 4 to 6). The horizontal measurement bar in each subplot depicts the mean duration of a crossing event in the respective phase to illustrate when a pedestrian finished their crossing and reached the other side of the road ("Pedestrian first", *early*: 3.568 s, *intermediate*: 4.264 s, *late*: 4.225 s; "Vehicle first", *late*: 4.702 s); e)–h) Vehicle-pedestrian distance before crossing event sorted by resolution in different phases of the interaction.

the drivers initiated communicating their yielding intention implicitly (i.e., started increasing $\dot{\tau}$). The lineplot of $\dot{\tau}$ indicates a slower increase of $\dot{\tau}$ reaching a lower maximum level compared to the baseline. The mean vehicle-pedestrian distance at pedestrian crossing initiation in *intermediate* crossings was 26.19 m, as shown in Figure 10f). For "Pedestrian first" resolutions in the *late* phase, the lineplot of $\dot{\tau}$ in Figure 10c) shows that the implicit yielding cues that the pedestrian perceived from the vehicle before the crossing event were independent of the condition and that they were similar comparing both conditions. The time between the moment at which $\dot{\tau}$ started to increase and the crossing event was around 6.6 s for both conditions. Compared to *intermediate* crossings, the implicit communication by means of $\dot{\tau}$ was stronger in *late* crossings. As illustrated in Figure 10g), the mean distance between vehicle and pedestrian at crossing initiation in *late* crossings was 18.45 m. The plots in Figure 10d) and Figure 10h) present the behavior for interactions that were resolved in the *late* phase with "Vehicle first". On average, the pedestrians started crossing when the vehicle passed them by 20.06 m. The lineplot of $\dot{\tau}$ in Figure 10d) shows that $\dot{\tau}$ was constant at -1 before the crossing event in both conditions.

In the *early* phase of an interaction, when the vehicle was further away and the traffic participants have not interacted with each other yet, pedestrians made their decision without being influenced by the system. In *early* crossings, the drivers barely showed any implicit signs of yielding ($\dot{\tau} = -1$) before the crossing initiation of the pedestrian. The lacking implicit communication in that phase does not mean that the drivers were not willing to yield or that they would not have indicated their yielding intention a few seconds later. Instead it could rather be interpreted in a way that the pedestrians made their decision independent of the vehicle and decided to resolve the interaction even when the driver was not communicating any yielding cues. In general, our findings regarding *early* crossings followed the results of Schroeder et al. (2014); Tian et al. (2023, 2025), that in the first stage of an interaction pedestrians make their crossing decision based on the traffic gap. After the crossing initiation, $\dot{\tau}$ started to increase, which indicated implicit yielding cues which became visible for the pedestrian. On the one hand, braking prevents a possible collision. On the other hand, this behavior could be interpreted as communicating the drivers' compliance with the pedestrian crossing decision and emphasizing their yielding intention. In the baseline condition, the results provided evidence for the bimodal distribution of *early* crossings and *late* crossings, which aligns with the findings of previous studies (Haq et al., 2024; Lee et al., 2025; Tian et al., 2023). The cHMI broke this bimodal pattern and significantly increased the amount of "Pedestrian first" resolutions in the *intermediate* phase of an interaction. The results suggest that at some point the driver began to communicate their yielding intention. Approximately 3 s after the start of the implicit communication, indicated by the increase in $\dot{\tau}$, the pedestrian initiated their crossing. This reaction time seemed similar in both conditions. The results suggest that if a pedestrian refused to cross in the *early* phase they needed clear signals from the vehicle in order to still decide to cross before the vehicle. This finding was again in line with the model proposed by Schroeder et al. (2014) and confirmed the findings of Tian et al. (2023, 2025). The implicit communication in *intermediate* crossings appeared to be similar in both experimental conditions with slight variations – $\dot{\tau}$ increased slightly faster in the baseline and reached higher values than with cHMI. This indicates that in principle drivers know how to communicate their intention implicitly and they do it similarly whether with or without the cHMI, but they need to be aware of the cooperation opportunity in order to

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achieve the observed benefit for the pedestrian. Although less interactions were resolved in the *late* phase with the cHMI, the system significantly increased the number of "Pedestrian first" resolutions from all interactions that were not resolved before in the *early* of *intermediate* phase. In the *late* phase, the implicit communication from the driver to the pedestrian before the crossing event was similar across the two conditions. This suggests that, besides the fact that more pedestrians crossed before the vehicle, the cHMI did not influence the way how drivers communicated implicitly and how pedestrians made their crossing decision in relation to the vehicle behavior. However, comparing the implicit communication before the crossing event in the *late* phase with the implicit communication in the *intermediate* phase, the results showed a longer period between the begin of the yielding communication and the crossing initiation. This finding indicates that pedestrians require stronger yielding cues in a later phase of the interaction, which might be related to the shorter vehicle-pedestrian distance at the crossing event. Before the crossing event, the drivers have already reduced the distance more, hence, stronger communication is necessary for the pedestrians to confidently cross the road.

Appendix D Learning effects during the experiments

Each participant pair conducted several runs of the experiments in both conditions, contributing multiple data points to the full dataset. We accounted for the dependency between data points by fitting LMMs and GLMMs including random intercepts and random slopes (where the data allowed). However, due to the repetition of similar experiments, certain behavioral patterns could have established across the whole set of tests. To investigate whether such patterns had a confounding influence on the overall results, we analyzed the data for possible learning effects.

We conducted an analysis for a possible learning effect regarding the eHMI. For each participant pair, we counted and accumulated the number of interactions in the cHMI condition that had a "Yielding"/"Stopping" message on the eHMI before the crossing initiation of the pedestrian. These can be considered as interactions in which the pedestrian had the opportunity to see and learn the meaning of the eHMI. Since the behavior of both participants in an interaction had an influence on the activation of the eHMI, especially the driver's compliance with the iHMI, the total number of interactions with eHMI "Yielding"/"Stopping" messages before the crossing event varied for the participants pairs. Figure 11 shows that among all pairs that had at least one interaction where the pedestrian was shown a "Yielding"/"Stopping" message before crossing, the proportion of "Pedestrian first" resolutions was 72.73 % in the first interaction the pedestrian was exposed to a "Yielding"/"Stopping" message before crossing. This proportion is already much larger than the general proportion of "Pedestrian first" resolutions in the baseline condition (see Figure 4), which underlines the effectiveness of the eHMI. Over the course of the set of experiments in the cHMI condition, further eHMI activations occurred. Figure 11 depicts that there was a learning effect from the first to the last interaction with an eHMI activation before crossing. The more often a pedestrian was exposed to a "Yielding"/"Stopping" signal, the higher the probability that an interaction was resolved with the pedestrian crossing first. From the fifth interaction with an external "Yielding"/"Stopping" message, the proportion of interactions resolved with "Pedestrian first" was 95 % or higher. Notably, from the seventh interaction, the proportion increased to 100 %.

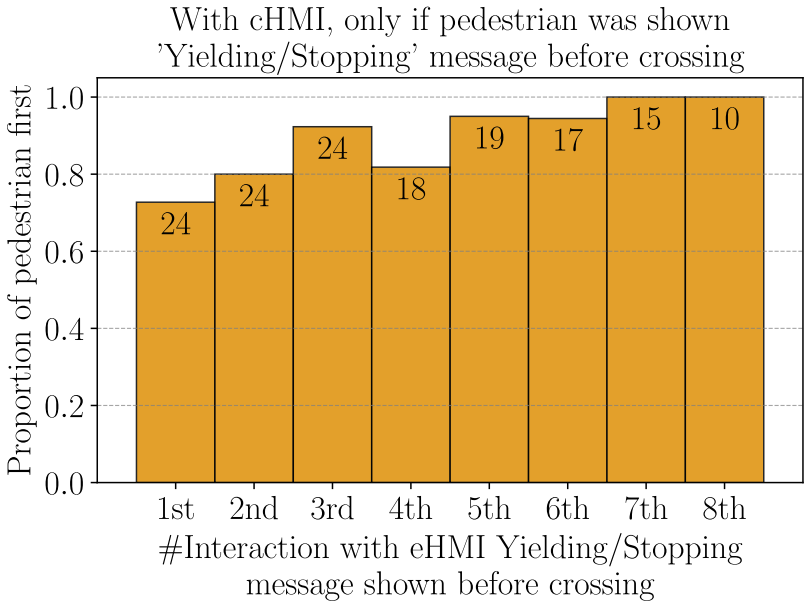

Figure 11: Proportion and absolute numbers of situations with cHMI resolved by "Pedestrian first" over the number of interactions that had at least one eHMI activation showing a "Yielding"/"Stopping" message before crossing. The number of interactions were accumulated individually per participant pair.

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There were 10 pairs where the pedestrians saw a "Yielding"/"Stopping" message before crossing in all 8 interactions. All of these respective eighth interactions with eHMI activation resulted in "Pedestrian first". Additionally, out of the 10 pairs, 9 pairs resolved all 8 interactions with "Pedestrian first". However, the observed effect could not be isolated from a general tendency of an increasing number of "Pedestrian first" resolutions in later interactions. We found that the upward trend towards more "Pedestrian first" resolutions was mostly created during the interactions of the first test block. Independent of the experimental condition, 40 % of first interactions in the first test block were resolved with "Pedestrian first", whereas this proportion increased to 61.29 % in the eighth interaction of the first test block. Due to counterbalancing the experimental conditions in the order of test blocks, this increasing tendency to resolve interactions with "Pedestrian first" in the first block affected both conditions similarly. We further investigated the test blocks (first block vs. second block) for a possible influence on the outcome. The left plot of Figure 12 illustrates that the proportion of "Pedestrian first" resolutions in the cHMI condition was nearly identical in both test blocks, which was also indicated by fitting a GLMM with random intercept ($N = 266$, Intercept $= 1.952$, $\beta = -0.0002$, $SD = 0.265$, $z = -0.0009$, $OR = 0.9998$, $p = .9993$, 95% $CrI = [-0.519, 0.518]$. This proportion was similar to the overall proportion of "Pedestrian first" resolutions with the cHMI. As can be seen in the right plot of Figure 12, in the baseline condition a strong difference existed between the first and the second experimental block regarding the outcome of situations. If participants first experienced the cHMI, they had a strong tendency to resolve situations with "Pedestrian first" in the second test block as well. However, if the participants started with the baseline condition, hence, experienced regular interactions without cHMI support in an untrained condition, only a small portion of situations were resolved with "Pedestrian first" ($N = 258$, Intercept $= -1.553$, $\beta = 2.72$, $SD = 0.271$, $z = 10.028$, $OR = 15.18$, $p < .001$, 95% $CrI = [2.188, 3.252]$). To further verify the effect of the test order, we fitted a GLMM for all experiments ($N = 524$) and added both experimental condition and test order as fixed effects including an interaction term $condition * test_order$. Again, random effects were modeled with random intercept for each participant pair and random slope for experimental condition. The Intercept $= -1.175$ of this model (baseline condition + first block) indicated a low probability for interactions resulting in "Pedestrian first". Note that this intercept was even lower than the baseline intercept when investigating the effect of the experimental condition only (see Section 3). This showed that the experiments were less likely to be resolved with "Pedestrian first" when the participants experienced the baseline condition in the first block than the overall likelihood in the baseline condition. The model indicated a strong effect of both experimental condition and test order ($\beta_{\text{condition}} = 2.573, SD_{\text{condition}} = 0.192, z_{\text{condition}} = 13.399, OR_{\text{condition}} = 13.1, p_{\text{condition}} < .001, 95\%\ CrI_{\text{condition}} = [2.196, 2.949]$ and $\beta_{\text{test_order}} = 1.993, SD_{\text{test_order}} = 0.185, z_{\text{test_order}} = 10.787, OR_{\text{test_order}} = 7.34, p_{\text{test_order}} < .001, 95\%\ CrI_{\text{test_order}} = [1.63, 2.356]$). The random effects intercept indicated substantial between-pair variability in baseline performance ($SD = 2.151$). The random slope suggested modest variability regarding the effect strengths of the cHMI across the participant pairs ($SD = 0.38$). The interaction between condition and test order was negative ($\beta_{\text{cond.*order}} = -1.016, SD_{\text{cond.*order}} = 0.262$), indicating that the increase associated with the cHMI was larger in the first block than during the second test block

$$\begin{aligned}\Delta\eta_{\text{first_block}} &= \eta_{\text{first_block,cHMI}} - \eta_{\text{first_block,baseline}} \\ &= (\text{Intercept} + \beta_{\text{condition}}) - (\text{Intercept}) = 2.573\end{aligned}$$

and

$$\begin{aligned}\Delta\eta_{\text{second_block}} &= \eta_{\text{second_block,cHMI}} - \eta_{\text{second_block,baseline}} \\ &= (\text{Intercept} + \beta_{\text{condition}} + \beta_{\text{test_order}} + \beta_{\text{cond.*order}}) - (\text{Intercept} + \beta_{\text{test_order}}) = 1.561\,.\end{aligned}$$

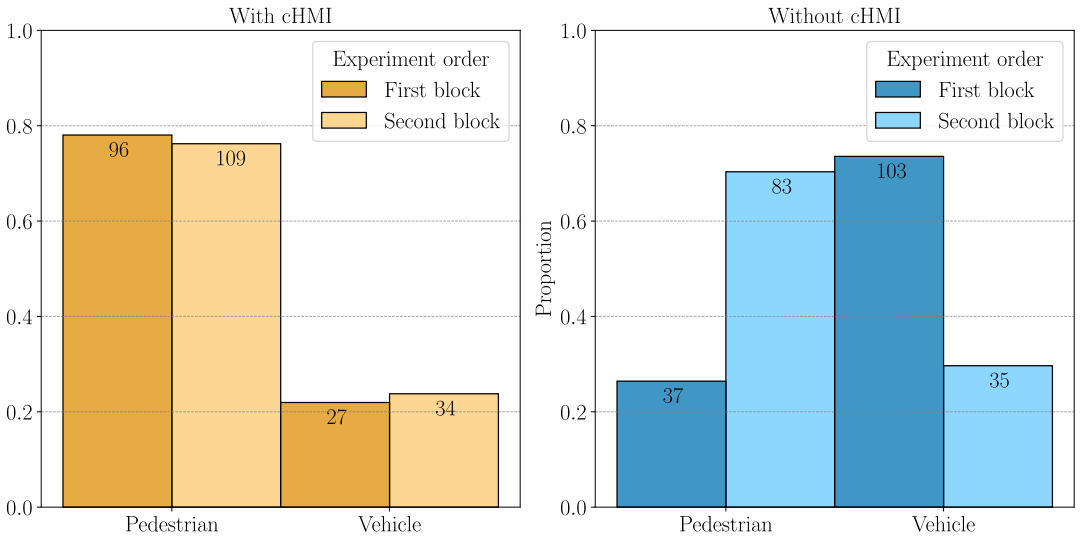

Figure 12: Proportion and absolute numbers of situations resolved by pedestrian/vehicle crossing first with cHMI (left) and in the baseline condition (right) sorted by order of experiment blocks.

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However, in the second block most interactions were resolved with "Pedestrian first". The results confirmed the generally strong effect of the cHMI independent of the experimental order and also showed that the odds of "Pedestrian first" with cHMI in the second block were high. Thus, the negative interaction term, which indicated a less pronounced effect of the cHMI in the second test block, was due to the higher odds for "Pedestrian first" in the baseline condition in the second block. This suggests that the cHMI biased the participants to this type of resolution even if there was no cHMI in the second block. Our analysis of the cHMI effect on driver behavior in Section 3.1 indicated a strong correlation between driver braking and "Pedestrian first" resolutions (see Figure 8 and Table 3). Hence, we conclude that a major contribution to the effect came from the drivers who were biased to braking by the cHMI. We interpret the learning effects between the test blocks and with the number of conducted trials mostly as a matter of trust calibration towards the drivers, who were more likely to yield, than towards the eHMI. Note that the learning effect mostly lead to more crossings in the baseline condition, artificially inflating the number of "Pedestrian first" resolutions in the baseline. Since the proportion of "Pedestrian first" resolutions in unbiased scenarios was even lower than the overall proportion of "Pedestrian first" resolutions without cHMI, this effect would only strengthen our message regarding the general effectiveness of the cHMI.

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