Designing cooperative interaction of automated vehicles with other road users in mixed traffic environments

interACT D.6.3. Impact assessment of the new interaction strategies on traffic cooperation, traffic flow, infrastructure design and road safety

Work package	WP6: Evaluation & Impact Assessment of Human-Vehicle Interaction
Task(s)	Task 6.3. Assessing the impact of the new human-vehicle interaction strategies and means on road safety, traffic low and city infrastructure
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Revision and history chart

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0.2	03/03/2020	Ruth Madigan; Yee Mun Lee, Christian Pek	Glossary of terms, List of abbreviations and acronyms, Executive Summary, Chapter 1, Section 3.1 and 3.2
0.3	04/05/2020	Yee Mun Lee, Christian Pek, Evangelia Portouli, Gustav Markkula, Jami Pekkenan	Amalgamated all Sections
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Glossary of terms

Term	Description
Addressed messages	Messages that are provided to one or more specific TPs
Non-addressed messages	Messages that are provided to everyone in the environment
Automated vehicle (AV)	Vehicle that provides automation of longitudinal and lateral vehicle control and can free the driver from the driving task – at least in some driving situations
eHMI/external HMI	Human Machine Interface that is presented on the vehicle to provide information to the surrounding traffic participants
Other traffic participants	Other road users in the environment such as cyclists, pedestrians, cars, trucks etc.
Use Case	Functional description of the behaviour of the AV in a traffic situation
Scenario	Description regarding the sequences of actions and events performed by different actors over a certain amount of time
Mixed Traffic	Usually referred to traffic consisting of different types of road users
Vulnerable Road Users	Road users with a higher fatality rate per accident than other groups, such as pedestrians, cyclists, motorcyclists

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List of abbreviations and acronyms

Abbreviation	Meaning
AVs	Automated Vehicles
CCPU	Cooperation and Communication Planning Unit
VR	Virtual Reality
VE	Virtual Environment
eHMI	External Human Machine Interface
iHMI	Internal Human Machine Interface
TTC	Time to Collision
TP	Traffic Participant
HMI ECU	HMI – Executive Control Unit
DGPS System	Differential Global Positioning System
WoZ	Wizard of Oz
LED	Light-emitting-diode
D	Deliverable
WP	Work Package
SAE	SAE International (initially established as Society of Automotive Engineers)
VRU	Vulnerable Road User
TTA	Time to Arrival
TDMs	Threshold Distribution Models
VDDMs	Variable-Drift Diffusion Models
HIKER	Highly Immersive Kinematic Experimental Research
HMD	Head-Mounted Display

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TTR	Time to React
TTB	Time to Brake
TTS	Time to Steer
TTK	Time to Kickdown
CV	Conventional Vehicle
ICS	Inevitable Collision States

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Executive summary

The interACT project aims to understand how interactions unfold between road users, in order to ensure the safe integration of automated vehicles (AVs) into mixed traffic environments. This document describes the final evaluation of the expected impacts of the interACT solutions in terms of traffic safety, flow, road design and road users' subjective experience of AVs. This analysis is based on the interACT communication solutions developed through earlier work packages, namely the CCPU (Cooperation and Communication Planning Unit) and safety layer developed in WP3, the eHMI signal designs developed in WP4, and the prototype vehicles developed in WP5. The underlying research questions, and methods to generate appropriate data for the modelling, are presented and discussed. The work of Work Package (WP) 6 reported in this Deliverable provides the final evaluation of the likely impact of AV interaction solutions on a societal level.

Chapter 2 presents computer simulations of the traffic flow efficiency impact of the interACT solutions, based on quantitative models of human-AV interactions at pedestrian crossings. The simulation results show that the inclusion of eHMI indications of yielding intentions led to average time savings (or time loss reductions) of about 1 s per interaction, for both AVs and pedestrians. The combination of the eHMI with an optimised AV yielding behaviour led to a rise in time savings of up to 1.5 s for the AV, and up to 3 s for the pedestrian in some kinematics situations. Results presented in Chapter 3 show that the eHMI also seems to improve road users' evaluations of their perceived safety, along with leading to slightly elevated ratings of AV comprehension. Drivers' comments indicated that they relied on eHMI to make decisions, if it was present; otherwise, AV trajectories were used for intention judgement.

In Chapter 4, we explore the impact of the interACT safety layer and conclude that the formal methods used prove that the vehicle never causes an accident, no matter how vulnerable road users are moving. This has been realized by a set-based prediction of surrounding traffic participants and the generation of fail-safe manoeuvers of the automated system. These fail-safe manoeuvers ensure the availability of safe actions even if vulnerable road users behave unexpectedly. The evaluation of the safety layer is validated based on different (urban and highway) scenarios from the CommonRoad benchmark suite (see https://commonroad.in.tum.de/), and therefore takes the current road infrastructure into account.

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1. Introduction

1.1 Background, purpose and scope

1.1.1 Background

One of the main challenges facing the introduction of automated vehicles (AVs) is that they will have to interact with other road users, such as other manually driven cars, cyclists and pedestrians (as illustrated in Figure 1). It is therefore important to have a good understanding of the interactions arising between AVs, their on-board users, and other Traffic Participants (TPs), in order to enable the integration of AVs in complex and mixed traffic situations.

The purpose of the interACT project is to develop interaction concepts for AVs, enabling AVs to behave in an expectation-conforming manner. Within WP6, the external Human Machine Interface (eHMI) concepts developed in WP4 (see D4.1, Kaup et al., 2018 and D4.2, Weber et al., 2019) have been integrated into our vehicle prototype. These eHMIs provide a means of communication between the AVs and other TPs. In addition, the Cooperation and Communication Planning Unit (CCP Unit) and Safety Layer, developed within Work Package 3 (see D3.1, Drakoulis et al., 2018; and see D3.2, Markowski et al., 2019) of the project, have also been integrated into our vehicle prototype. The CCP Unit allows all interactions between the vehicle automation, on-board user and other TPs to occur in a time-synchronised manner. The proposed safety layer can eliminate or reduce the severity of the impact of collisions.

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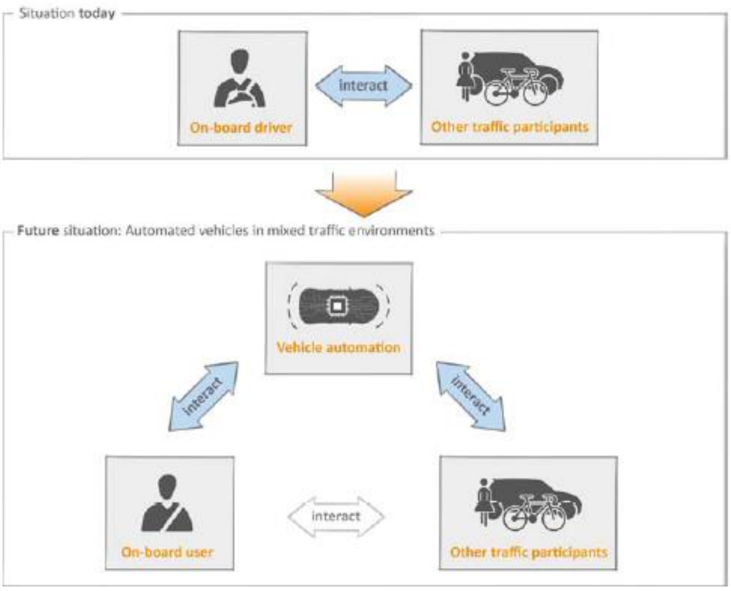

Figure 1: Illustrating the current interaction between on-board driver and other TPs (top). Illustrating the future interaction between AVs in mixed traffic environments (bottom).

1.1.2 Purpose and scope

The main objectives of this Deliverable is to evaluate the impact of the interACT prototypes and solutions on road safety, traffic flow, and road infrastructure requirements, as well as assessing how trust and acceptance of AVs is affected by the introduction of systems which allow better understanding of their intentions. It builds on the evaluation criteria identified through D6.1 (Lee et al., 2019), and the individual level results presented in D6.2 (Dietrich et al., 2020), along with the real-world observational data collected in WP2 (see D2.1 and D2.2, Dietrich et al., 2018; 2019).

Chapter 2 outlines how simulations with human interaction models were used to conduct an impact assessment of the interACT eHMI solutions on pedestrians' crossing decisions, crossing efficiency, and traffic flow, as well as subjective evaluations of safety and comfort. In Chapter 3, the effect of eHMIs on AV trust and comprehension was explored using questionnaires focusing on driver-AV interactions.

In Chapter 4 the interACT safety layer is evaluated using threat assessment models. This provides an assessment of the objective safety of the proposed fail-safe trajectory approach, along with providing objective and subjective measures of the criticality of the traffic scenarios explored.

Finally, Chapter 5 provides a summary of the conclusions reached through this Deliverable.

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1.2 Intended readership

This Deliverable provides insight into the estimated local and societal impact of the solutions developed through the entire interACT project for our Project Officer, the reviewers, and the European Commission, along with providing information for all interACT project partners about the ultimate impact of the interACT design solutions in terms of traffic efficiency, safety, and road user acceptance. In addition, this Deliverable is publicly available. Therefore, it is intended to provide information to stakeholders, other researchers and industrial partners who are interested in knowing knowing more about the project's approach to AV evaluation for external communication.

1.3 Relationship with other Work Packages

Deliverable 6.3 has received input from, and is closely linked with, other Work Packages (see **Figure 2**). The prototypes that were integrated within **WP5** 'Integration, Testing and Demonstration' were evaluated (See Deliverable 6.2 for more information) and the results of this evaluation tested with Threat Assessment models. The two interACT prototypes — the BMW i3 and CRF Jeep Renegade — have integrated the 'Suitable HMI for successful human-vehicle interaction' developed in **WP4**, and the CRF prototype also integrated the **WP3** 'Cooperation and Communication Planning Unit', which includes the interaction planning and executive of the prototype.

The methodologies used in **WP2** 'Psychological Models on Human Interaction and Intention Recognition Algorithms' to investigate interactions between current road users (see Deliverable 2.1, Dietrich et al., 2018; and Deliverable 2.2, Dietrich et al., 2019), and those used in **WP4** to investigate road users' reactions to HMI solutions (see Deliverable 4.2, Weber et al., 2019), were used to develop appropriate evaluation models, and to provide insights into the likely impacts of the interACT solutions in real-world contexts.

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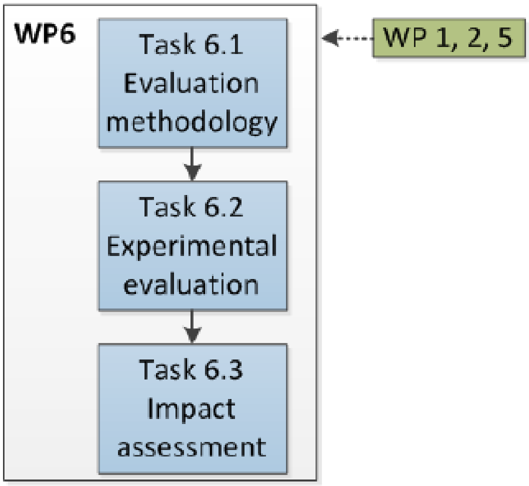

Figure 2: Relationship with other interACT Work Packages

In the next section, we provide an overview of the computer simulations used to evaluate the traffic flow efficiency impact of the interACT solutions.

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2. Simulations with human interaction models

2.1 Background and objectives

One of the goals of interACT has been to develop quantitative models of human road user behaviour, and apply these in virtual testing simulations of the types of AV interaction strategies developed in interACT. These objectives were described in some detail in interACT Deliverable D2.1, together with results of the first model development (Dietrich et al., 2018) and a first full set of model development and validation results were provided in Deliverable D2.2 (Dietrich et al., 2019). See also the corresponding publications (Markkula et al., 2018; Giles et al., 2019). Models were developed and tested for the two "road crossing" scenario types shown in Figure 3, with the modelled human behaviour being the crossing decision of road user C, as a function of the behaviour of the approaching road user A (human or automated). Before interACT, models of human behaviour in these types of crossing scenarios have typically been focused on the relatively high-level question of "gap acceptance", i.e., whether crossing road users will reject or accept a given gap between two non-yielding vehicles (e.g., Sun et al., 2003; Davis and Swenson, 2004; Papadimitriou et al. 2009; Ashalatha and Chandra, 2011) and more recently also considering yielding vs non-yielding vehicles (Fricker and Zhang, 2019). However, given interACT's focus on the *quality* of the interaction between AV and human, more detailed-level models were desired, which would predict not only *if* a gap is accepted, but also (1) *when* the road user would start crossing in that accepted gap, and (2) what the impact on this timing would be of not simply *whether* the other road user yielded, but also of *how* they yielded, in terms of exact deceleration behaviour and any eHMI signals.

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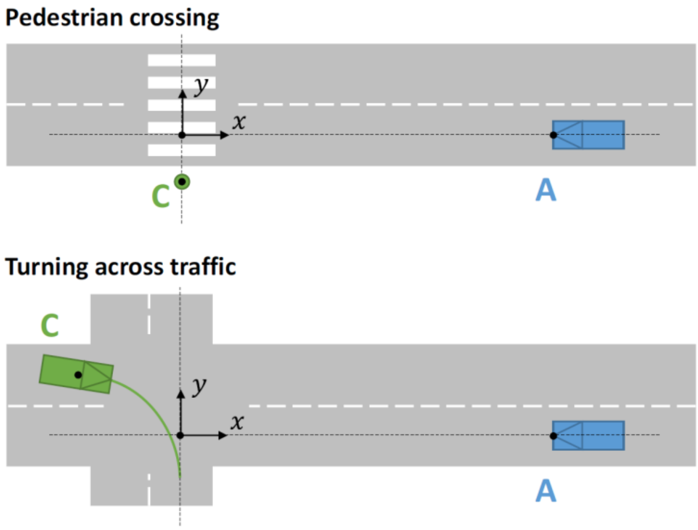

Figure 3: The two road crossing scenarios for which human behaviour models were developed in interACT WP2.

In interACT WP2, the focus was on AV deceleration behaviour (not eHMI), and two different types of models were investigated: threshold distribution models (TDMs) and variable-drift diffusion models (VDDMs). These are described in detail in Deliverable D2.2 (Dietrich et al., 2019), but will also be summarised briefly further below. In the WP2 work, the VDDMs were found to be difficult to reliably fit to data, and the TDMs produced satisfactory results. Therefore, the final model delivery from WP2, in the form of a publicly available model simulation software tool (https://osf.io/pweq5/), relied on the TDM formulation. For this model, parameterisations were provided, and shown to reproduce human crossing behaviour of UK and Japanese road users, as observed in a VR study, which will also be briefly summarised further below.

In the interACT WP6 work reported here, we had two main goals, as set out in Deliverable D6.1 (Lee et al., 2019):

- Extend the WP2 crossing decision models:
  - To properly account for effects of vehicle distance that were not captured well in the WP2 models.
  - To also take into account eHMI indications about yielding from an approaching AV, something which was not addressed in WP2.

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- Run simulations with the models, to estimate the impacts of AV interaction strategy in these yielding scenarios, on crossing decisions, interaction efficiency, and subjective safety[1]. Specifically, we aimed to estimate the impact on these outcomes of two of the design strategies advocated in interACT (Weber et al., 2019) (1) presence of eHMI for indicating yielding, and (2) a yielding deceleration behaviour optimised for being easy to understand for the crossing road user.

In the sections below, the two investigated model types will first be introduced briefly. Then, the human behaviour data used to parameterise and test the models will be described, and results from the novel model-fitting work carried out in WP6 will be briefly presented. Finally, the model simulations carried out with the models will be described, and the obtained impact assessment results will be presented and discussed.

2.2 Models

Both model types investigated in interACT WP2 and WP6 are described in detail in Deliverable D2.2 (Dietrich et al., 2019). Briefly put, both types of models assume that crossing road users take into account a number of different time-varying perceptual inputs about the kinematic traffic situation, such as the distance to the approaching vehicle, its apparent time to arrival (TTA; distance divided by speed), as well as the time derivative of TTA (which is a perceptually available indicator of deceleration). These input quantities are combined into a single “generalised TTA” by means of an algebraic function, including a number of model parameters.

In the threshold distribution model (TDM) formulation, this generalised TTA is then compared to a lognormal distribution of generalised TTA thresholds, modelling the thresholds assumed to be present in a population of road-crossing humans. At each time step, road-crossing is triggered for the fraction of the population with thresholds lower than the currently observed generalised TTA. These triggers are then convolved with an additional lognormal “reaction time”, to yield the final crossing onset distribution.

[1] We initially intended to also study impacts on objective safety, in terms of frequency of harsh decelerations needed as a function of AV interaction strategy. If one considers this research question in more detail, however, one realises that there is no sensible AV yielding strategy where the AV would not at least aim for a full stop before the crossing road user, which means that in practice there are no situations where the crossing road user can cause the need for harsh deceleration for an already yielding AV. In future work, one could consider using the models developed here to see what the risk of harsh decelerations would be in situations where the AV decides **not** to yield for whatever reason; this type of investigation is however outside of the interACT scope.

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In the variable-drift diffusion model (VDDM) formulation, the generalised TTA is instead processed in "drift diffusion" (or "evidence accumulation") decision-making unit, where it is integrated together with random noise, up to a threshold at which the crossing decision is made.

These VDDMs are attractive in that they are mechanistic models, with strong support from psychological and neuroscientific work, but they are more difficult to fit to data than the TDMs, which prompted us to focus on TDMs in interACT WP2. However, in the interACT WP6 work, we focused on the pedestrian crossing scenario only, considering also data from a new and larger experiment. We also reduced the VDDM complexity to a single-accumulator model only (whereas in WP2 we also tested more complex multiple-accumulator VDDMs), and we leveraged the more advanced model fitting methods described by Shinn et al. (2020). This allowed us to achieve consistent fits also with the VDDMs.

2.3 Human behaviour data and model fitting results

As mentioned, in interACT WP2, a VR experiment, using a head-mounted display (HMD) was carried out, with both UK and Japanese participants, who used a button press to initiate pedestrian crossing and vehicle turning in the scenarios depicted in Figure 3. See interACT deliverable D2.2 (Dietrich et al., 2019; see also Giles et al., 2019) for a full description of this dataset, and a presentation of the results obtained when fitting TDMs and the first iteration of VDDMs.

In the present WP6 work, we also made use of a more recent dataset, collected in the new University of Leeds HIKER (Highly Immersive Kinematic Experimental Research) lab, a "CAVE" type pedestrian simulator. Participant pedestrians walked freely in this simulator, to carry out road crossings when they deemed it safe to do so between two approaching vehicles, where the second vehicle would sometimes keep a constant speed, other times decelerate, and for some participants the approaching vehicle also provided eHMI signals when it was yielding. For a complete description of this dataset, see Lee et al. (2020).

Since the original HMD experiment provided a better variety of kinematic scenarios, we fitted the kinematics-related parameters of the TDM and VDDM to this dataset. Figure 4 shows that, thanks to an improved treatment of distance information, the models are now, capable of capturing the tendency of human participants to more easily accept a given time gap, if the distance gap is larger (i.e., because the approaching vehicle is travelling at a higher speed; Dietrich et al., 2019). The left panel of Figure 6 shows the overall model performance, across all scenarios in the HMD dataset.

Next, we applied the fits obtained from the HMD dataset to the scenarios without eHMI in the CAVE dataset. As illustrated in the left panel of Figure 5, and in the right panel of Figure 6, we found that the

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human crossing onsets in the CAVE experiment were generally well-predicted by the model, effectively providing a validation of the model with respect to its handling of scenario kinematics. Then, we also fitted an additional model parameter to account for the effect of eHMI indications of yielding, and as shown in the right panel of Figure 5, we found that this allowed the model to capture the effect of earlier human crossing onsets, in the presence of eHMI (e.g. De Clercq et al., 2019).

Overall, we found that the TDM provided a slightly, but not substantially, better fit of the HMD dataset than the VDDM, whereas the VDDM was more successful at predicting the human data in the CAVE dataset. Full details about these improved models and fitting results will be provided in a forthcoming paper (Pekkanen et al., 2020).

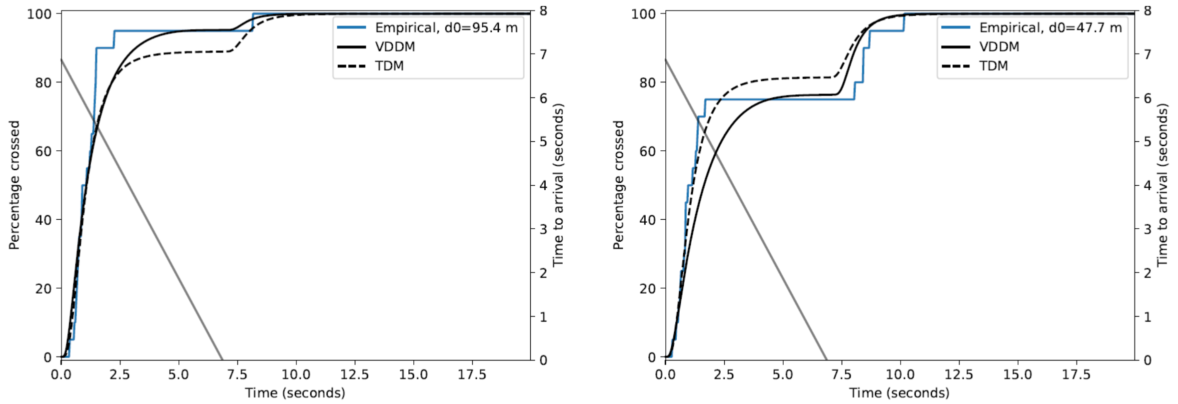

Figure 4: Human participant crossing onset times (blue) versus VDDM and TDM fits, for two different constant-speed scenarios in the HMD pedestrian crossing experiment, with identical time to arrival of the approaching vehicle (7 s), but differing initial distances (95.4 m vs 47.7 m).

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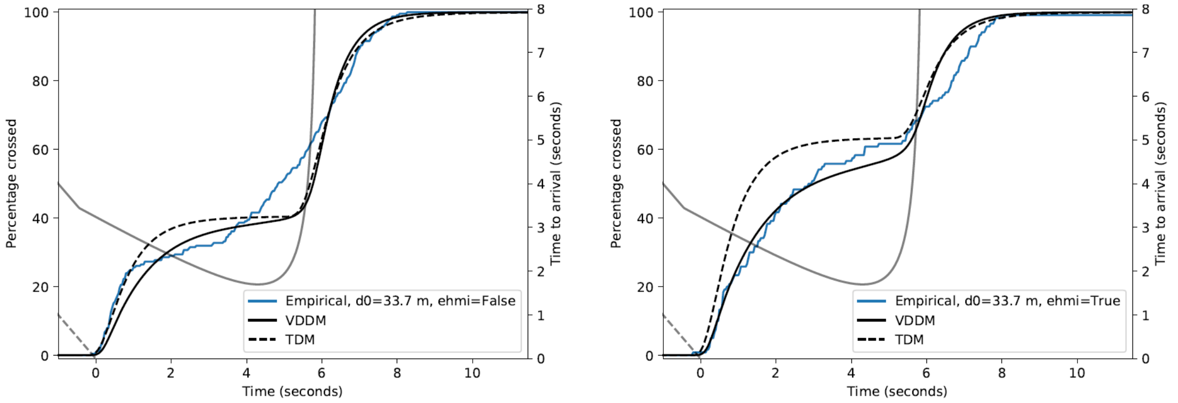

Figure 5: Human participant crossing onset times (blue) versus VDDM and TDM fits for two scenarios in the CAVE experiment that are kinematically identical, but with an eHMI indication of yielding being present in the scenario shown to the right.

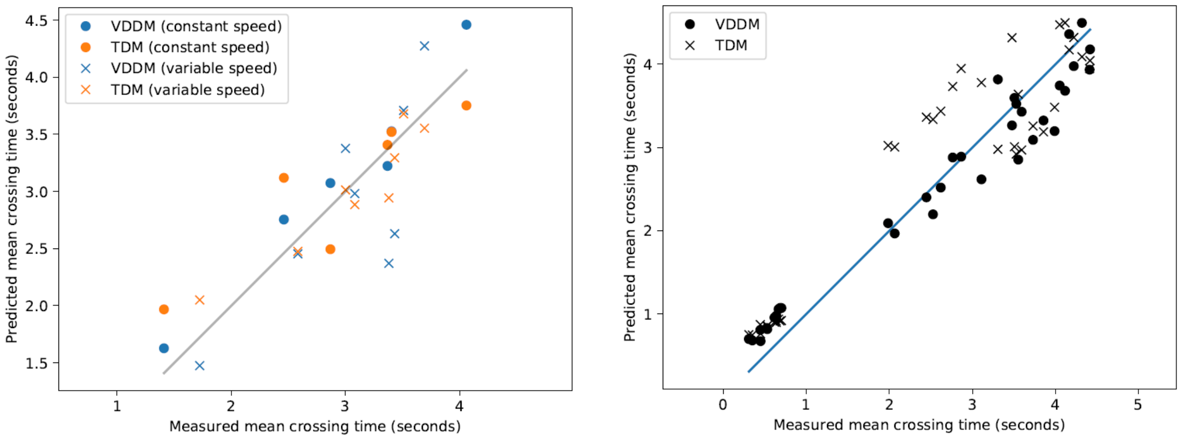

Figure 6: Overall performance of the models, in terms of the average crossing onset times, across all scenarios in the HMD experiment (left) and the CAVE experiment (right).

2.4 Impact assessment simulations and results

To investigate the impact of AV interaction design on the quality of interactions with human road users, we ran simulations with the models developed in interACT WP2 and WP6. Our main emphasis here was on the most recent iteration of the VDDMs, fitted to the UK pedestrian crossing HMD, and CAVE experiments, since with this instantiation of our models we could predict effects not only of AV

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movements, but also of eHMI indications. The results obtained with the TDMs were qualitatively similar. For completeness, we also report results from some complementary simulations with the interACT WP2 TDMs, as fitted to the UK/Japan HMD experiment on pedestrian crossing and driver turning.

2.4.1 Crossing decision, efficiency, and traffic flow

As mentioned above, the general pattern with respect to the crossing decision of a crossing road user is that this decision will come quicker the more obviously a yielding AV is signalling its yielding intentions, which in turn has an impact also on how quickly the yielding AV can progress past the interaction. Thus, there are clear efficiency and traffic flow implications of the specific yielding behaviour adopted by AVs. Crucially, the models developed here provide precise predictions of how much quicker crossing decisions come as a function of the specific ways in which the AV is signalling its intentions.

Our baseline scenario, here, was one where the AV yields without any eHMI indication, applying the minimum constant deceleration needed to stop at the pedestrian crossing, with a 2.5 m margin to the pedestrian's location (corresponding to stopping around 1 m in front of a 3 m wide zebra crossing which the pedestrian is crossing along the midline). Figure 7 shows the model-predicted average *time losses* for this baseline scenario, both for the AV and the pedestrian, as a function of initial AV speed, and initial TTA (time left for the AV to the pedestrian crossing), when the pedestrian appears at the pedestrian crossing. Note that for simplicity we are here considering a scenario where the pedestrian (or the pedestrian's intent to cross) is detected by the AV at a point in time when the pedestrian is already at the crossing location, ready to cross.

These time losses are defined as the delay in time with which each road user will arrive at their destination as a result of the interaction, i.e., how much later they will arrive compared to if they had been alone on the road, and could have continued ahead, unimpeded. In the case of the pedestrian, who always starts from standstill (and is assumed to need 3 s to cross the AV's path), the time loss in the interaction is exactly equal to the crossing decision time. For the AV, where a maximum positive acceleration of 1.3 m/s^2 to regain the initial speed was assumed after the pedestrian crossed the road, the time loss is more complex, since it is also a function of how much the AV has had to reduce its speed, possibly even all the way to a standstill, while waiting for the pedestrian to decide to initiate, and complete the crossing.

As can be seen in Figure 7, predicted time losses are worst for the lower initial TTAs (e.g., TTA 5 s or lower), up to around 5-6 s time loss for the pedestrian, and 6-11 s time loss for the AV. The reason for this pattern is that at the lower initial TTAs, pedestrians will initially be very hesitant to cross, and will

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often wait until the AV has come to a complete stop before crossing. Figure 7 also shows that there are non-trivial interactions between initial TTAs and initial speeds on time losses, both for the AV and the pedestrian. As explained above, both TTA and speed separately affect the crossing decision timing, and there is also the added complexity of the AV needing to regain lost speed after the pedestrian has crossed.

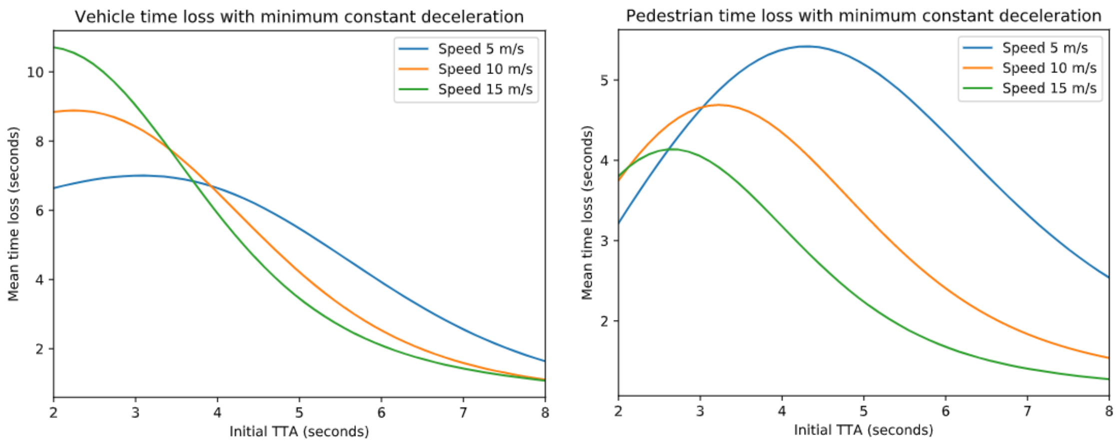

Figure 7: Model-predicted average time losses for the AV (left) and pedestrian (right), for the baseline AV behaviour of applying the minimum constant deceleration needed to stop at the pedestrian crossing.

We then varied the AV deceleration magnitude, and identified, for each initial AV speed and TTA, the deceleration at which the predicted time loss for the AV was minimal. This was calculated separately for yielding conditions both with and without an eHMI indication, provided at the same time. When the eHMI indication was provided, it was activated from the very start of the simulated scenario, i.e., as soon as the pedestrian appeared at the pedestrian crossing and the AV began decelerating[2]. Figure 8 shows the *reductions in time loss* (or, equivalently, time savings) from (1) just optimising deceleration, without including eHMI, (2) just including eHMI, and (3) doing both things at the same time. According to the model, compared to the baseline scenario, if the AV both applies optimal yielding deceleration and provides an eHMI indication of its yielding, average time savings are up to 1.5 s for the AV, and up to 3 s for the pedestrian. The time saved varies with the initial conditions, and is generally largest for

[2] The models could in theory also be used to predict effects of eHMI onset timing, but, in line with empirical data (De Clercq et al., 2019), the models will never predict that it is beneficial to delay eHMI activation, once the yielding decision is made. For this reason, we only studied scenarios with immediate eHMI onset.

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low initial AV speeds, and with initial TTAs in the 3-6 s range (i.e., coinciding with the range where baseline time losses tend to be the largest). The benefits of AV deceleration optimisation alone are most pronounced at lower initial TTAs, whereas the benefits of eHMI alone are most pronounced at higher initial TTAs, such that both features together provide time saving benefits across a wider range of situations. Excluding the deceleration optimisation is particularly detrimental for the pedestrian, for which maximum average time savings drop from about 3 s to about 1.2 s. In sum, including both optimised yielding deceleration and eHMI in an AV's interaction design seems recommendable.

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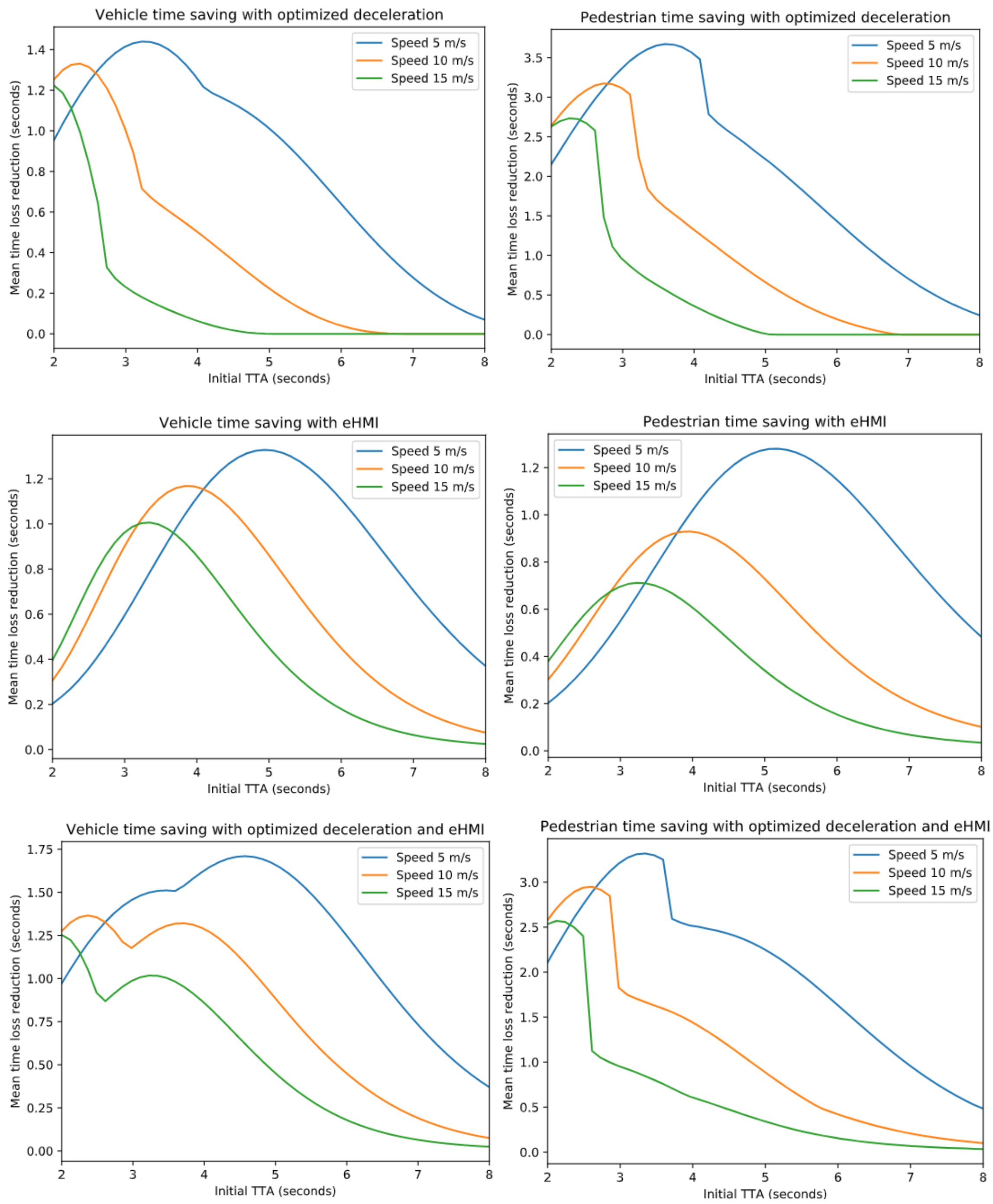

Figure 8: Model-predicted reductions in time loss in the pedestrian crossing scenario, for the AV (left panels) and the pedestrian (right panels), when just optimising AV deceleration magnitude (top panels), when just including an eHMI indicating yielding (middle panels), or both (bottom panels).

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Figure 9 shows AV yielding deceleration magnitudes as a function of initial speed and TTA, both for the baseline “minimum needed deceleration” yielding (dotted lines), and the optimised deceleration magnitudes minimising AV time loss, with and without eHMI (dashed and solid lines, respectively). It may be noted that, in many situations, the optimised deceleration magnitudes are not much higher than the minimum needed deceleration, but for higher speeds and lower TTAs, the optimised deceleration magnitudes increase. For example, at an initial speed of 5 m/s (18 km/h) and an initial TTA of 4 s, a situation where some of the highest time savings can be made by optimising deceleration according to Figure 8, the optimal deceleration magnitude is just under 2 m/s^2 without eHMI, and just over 1 m/s^2 with eHMI, as compared to the minimum needed deceleration of just under 1 m/s^2. These increases in deceleration magnitude seem acceptable a priori, but it would of course be recommendable to test this with actual human users. Overall, it can be seen from Figure 9 that, besides the further improved time savings, an added benefit of including an eHMI indication of yielding on top of deceleration optimisation, is that these time savings can be achieved by the AV with a smaller magnitude of deceleration, compared to the situation without eHMI; these lower deceleration magnitudes are likely to be beneficial from an AV user/rider acceptance point of view. As initial TTA values become small (i.e., the pedestrian appears at the crossing when the AV is already close to it in time), both the minimum, and especially the optimised, yielding decelerations reach levels that may not be acceptable; for these low TTAs the natural behaviour of the AV might be not to yield to a pedestrian who appears at a crossing.

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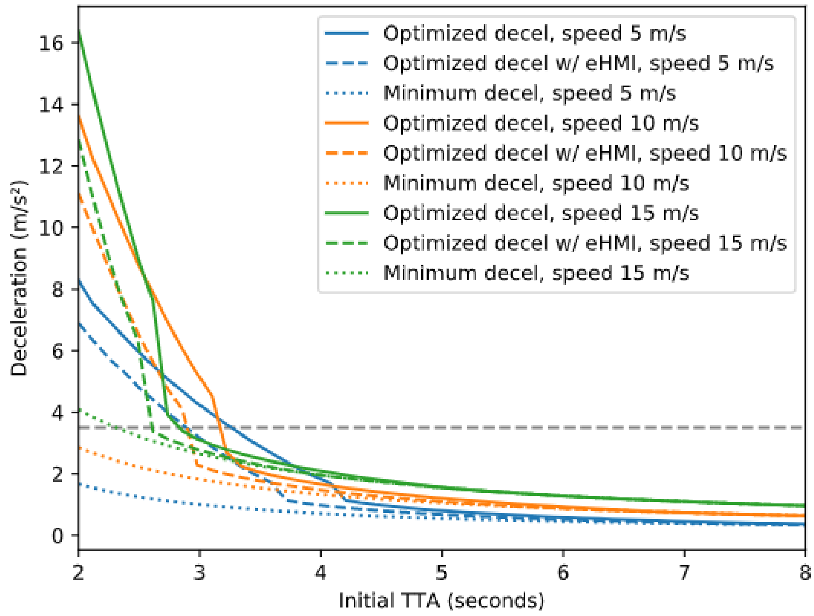

Figure 9: Yielding deceleration magnitudes as a function of initial AV speed and of how far the AV is from the pedestrian crossing when the pedestrian appears (initial time to arrival; TTA). The horizontal dashed line at 3.5 m/s^2 deceleration indicates a possible maximum level of acceptable deceleration.

We further investigated the impact of deceleration optimisation, by also running simulations using the TDM models fitted to the UK/Japanese HMD study. Since these simulations were not based on our final models and model-fitting methods, we content ourselves here with reporting qualitative results. Similar patterns to those reported above were obtained, and these simulations also allowed a comparison of the predictions for UK versus Japanese pedestrians, and for turning car drivers versus crossing pedestrians. As reported in Dietrich et al. (2019a), in the UK/Japan HMD experiment, car drivers in general adopted larger safety margins when turning than the safety margins adopted by pedestrians when crossing, and Japanese pedestrians/drivers in general adopted larger safety margins than UK pedestrians/drivers. The model simulations showed that these larger safety margins for drivers, as compared to pedestrians, and for Japanese road users, as compared to UK road users, resulted in (1) even bigger predicted time losses in the baseline (minimum needed deceleration) scenario, and, relatedly, (2) even bigger time savings could be obtained from optimising the yielding decelerations. In other words, even better time savings from optimising AV yielding deceleration than those reported in Figure 8 (for a UK pedestrian crossing scenario), are likely to be attainable in traffic scenarios and

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cultural contexts where larger safety margins are adopted (e.g., a UK driver turning scenario, or a pedestrian crossing scenario in Japan).

2.4.2 Subjective safety and comfort

In the pedestrian crossing experiment in the CAVE, we also wanted to investigate whether we were able to understand what determines the subjective safety (arguably related to comfort) that pedestrians perceive in a given road crossing. We therefore collected subjective safety ratings on a five-point Likert scale after each completed crossing, and attempted to fit regression models, explaining these ratings as a function of a number of different aspects of the individual crossing trials. Figure 10 shows the raw subjective safety ratings obtained, as well as the predicted averages from our regression model, as a function of presence or absence of the eHMI indicating yielding, and the maximum "criticality" experienced in the crossing, quantified as the maximum inverse of the apparent TTA (distance divided by time) perceived by the pedestrian 1 s before and during their crossing of the road. The 1/TTA factor accounted for a statistically significant ($p < .0005$) but—as can be seen in Figure 10—rather small part of the total variability in the data. As might have been expected, higher objective situation criticality was associated with lower ratings of subjective safety. There was also a non-significant trend ($p = .051$) of improved subjective safety ratings with eHMI present. The vertical stripes of data points in Figure 10 arise from trials with AV deceleration where the pedestrian crossed at a point in time such that the minimum apparent time to arrival (TTA) in the scenario occurred in the considered time interval around the crossing.

We conclude from this analysis that most of the variation in subjective safety ratings comes from factors that we did not successfully account for here, and for this reason we did not incorporate this regression model into our impact assessment model simulations, as we had originally considered doing. However, the results obtained here still suggest that small improvements in perceived safety may be achievable by avoiding small apparent TTA values. In other words, slightly exaggerated yielding decelerations, as discussed in the previous section, may thus also improve the subjective experience of AV safety, in addition to the efficiency/traffic flow gains reported above. Again, however, the matter of comfort for AV passengers also needs to be considered.

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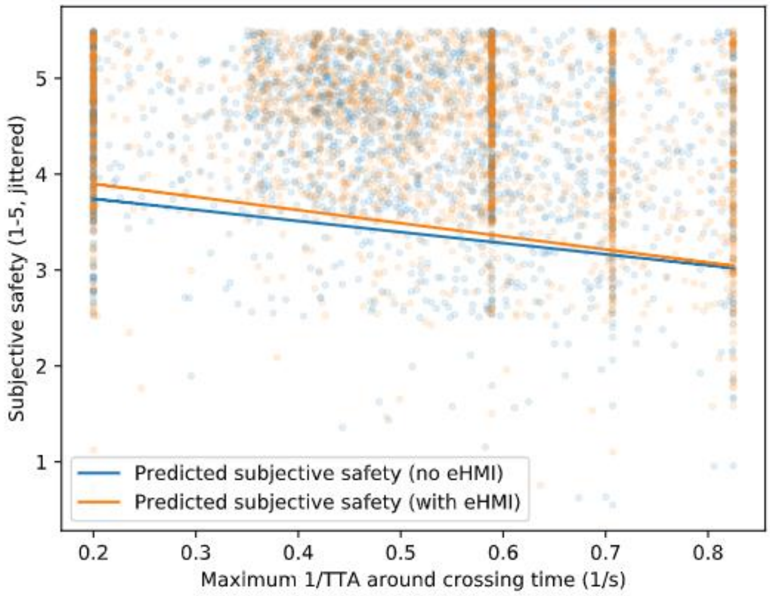

Figure 10: Subjective safety ratings as provided by the participants after each completed road crossing trial (dots) in the pedestrian crossing CAVE experiment, and predicted averages from a regression model fitted to these data (lines).

2.5 Conclusions

We have presented improved quantitative models of human-AV interactions at pedestrian crossings, extending on the models presented in interACT WP2 to now also be able to reflect the effects on human road-crossing behaviour of distance gap effects and eHMI indications, signalling AV intentions to yield. Thanks to these extensions, the models could be put to use to comprehensively evaluate the effect of interACT solutions on traffic flow efficiency in pedestrian crossing interactions.

Our simulations show that in a baseline scenario, assuming an AV design without eHMI, applying minimal deceleration to stop at the pedestrian crossing, results in variable time losses for the involved agents, changing substantially across different kinematic situations. The greatest time losses were predicted for situations where both initial AV approach speed and time to arrival (TTA) at the pedestrian crossing were low, up to 5-6 s time loss for the pedestrian and 6-11 s time loss for the AV, per interaction. We then applied the design solutions proposed in interACT for this scenario (Weber et al., 2019), and found that the addition of eHMI only led to average time savings (time loss reductions) compared to the baseline design, of about 1 s per interaction, for both AV and pedestrian. When

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combining the eHMI with an optimised AV yielding behaviour, average time savings rose, per-interaction, for some kinematic situations. This was up to 1.5 s for the AV and up to 3 s for the pedestrian. Therefore, from an efficiency perspective, a combination of both of these design features seems recommendable. Further studies are needed to elucidate AV rider acceptance of the optimised (increased) deceleration magnitudes. In this respect, another clear benefit of the eHMI feature is that the model-estimated optimal deceleration is somewhat milder when eHMI is present. We also analysed subjective data from one of the experiments included in the modelling work, and found that optimised deceleration magnitudes may additionally contribute to an improved subjective experience of safety in pedestrians.

The results just mentioned were obtained for models fitted to UK pedestrians. We also performed additional simulations with models from interACT WP2 fitted to behaviour of Japanese pedestrians, and to UK and Japanese drivers turning across traffic. The overall takeaway from these simulations was that in situations where larger safety margins are adopted (e.g., driver turning compared to pedestrian crossing; Japanese compared to UK road users) the time saving benefits of eHMI and optimised yielding deceleration were predicted to be bigger.

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3. Impact of external HMIs on comprehension and trust

Chapter 2 has provided an outline of computer based models developed to comprehensively evaluate the effect of interACT solutions on traffic flow efficiency in pedestrian crossing interactions. In Chapter 3, we focus on driver interactions with the interACT AV communication solutions. In particular, we aim to develop a deeper understanding of the impact of eHMI on drivers' comprehension of AV intended future behaviours, along with exploring how eHMI might affect drivers' trust in AVs.

3.1 Objective

The objective of the study was to study the impact of the interACT eHMI on comprehension of the AV's intention and trust in the AV by other drivers who interacted with an AV during a left turn at low speed.

3.2 Method

3.2.1 Location

The study took place at a parking lot of the National Technical University of Athens campus at Zografou, Greece, from 24 October to 8 December 2019, at afternoon hours when traffic is low and at good weather conditions.

3.2.2 Equipment

Two experimental vehicles were used, both driven by the same driving instructor. The first vehicle (Fiat Stilo) was driven normally (condition "Manual"). The second vehicle (Toyota Yaris Hybrid 2018 model) was driven via double pedals by the driving instructor who was seated on the co-driver's seat, no one was seated on the driver's seat. This simulated the autonomous vehicle, the "AV". The second vehicle was used either without any external HMI (condition "AV no eHMI") or with a LED stripe fixed on the external of its front dashboard (condition "AV with eHMI"). The LED stripe flashed according to the specifications for the interACT eHMI (D4.2; Weber et al., 2019).

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Figure 11: "AV" used in the ICCS study and LED stripe used as eHMI in the condition "AV with eHMI"

3.2.3 Setup

Two test setups were used with the following conditions:

Table 1: Test set ups for driver interaction study

Setup	Condition 1	Condition 2
Setup 1	Condition (1a): "Manual"	Condition (1b): "AV with eHMI"
Setup 2	Condition (2a): "Manual"	Condition (2b): "AV no eHMI"

Each driver in Setup 1 or in Setup 2 drove three runs per condition, for example: 1a, 1b, 1a, 1b, 1a, 1b; the order of conditions was randomized.

3.2.4 Participants

20 drivers, 10 male and 10 female participated in Setup 1 ("Manual" vs "AV with eHMI"). Their mean age was 40.4 years (min = 32, max = 53 years) and they had a driving license for a mean of 20.5 years (min = 12, max = 34 years).

20 drivers, 10 male and 10 female participated in Setup 2 ("Manual" vs "AV no eHMI"). Their mean age was 41.8 years (min = 30, max = 59 years) and they had a driving license for a mean 20.6 years (min = 7, max = 39 years).

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3.2.5 Procedure

When arriving, the drivers were told that they would participate in a study involving an autonomous vehicle, and they were instructed about the meaning of the LED stripe flashing. The whole experimental process was explained and they were familiarised with the "AV" driving with or without the LED stripe (depending on the Setup), via videos. The drivers were asked to drive their own vehicle on the green route depicted in the Figure 12. The driving instructor was driving on the orange route, both in the "Manual" and the "AV" conditions. An experimenter onboard the driver's vehicle instructed the driver when to start driving from position A. An external facilitator at position C synchronized both vehicles, so that they both started from the positions B and D at the same time. The distance between positions B and D was approximately 60 m. Red traffic cones were positioned at the crossing, so that simultaneous turning of both vehicles was not possible.

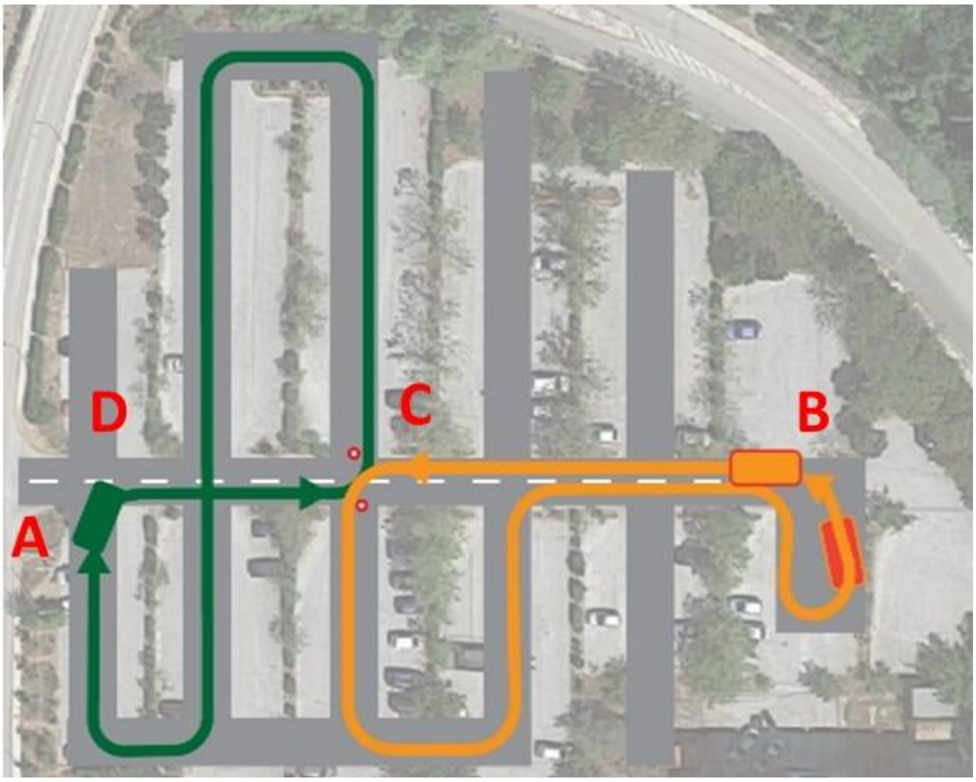

Figure 12: ICCS study location and routes

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3.2.6 Data collection

After the end of the driving, drivers were asked to complete a questionnaire about their understanding of the other vehicle's intention and their perceptions as regards the other vehicle and the eHMI. They were asked to rate, using a 4 point Likert-scale, their agreement to each of the following statements: "I waited more than usual to turn", "Yielding seemed realistic to me", "I understood the other vehicle's intention before it stopped", "I felt safe before and during turning", "The driver at the wheel made me feel safe" or "The AV's movement made me feel trust to the AV", and "The flashing yielding LED stripe made it easier for me to turn" or "I needed some yielding indication from the AV in order to decide". The participants were also asked to write a free commentary about their interaction experience and mention anything they considered important.

3.2.7 Data analysis

The participant responses to the Likert-scale questions in the questionnaire were coded as follows +2: Definitely Yes, 1: Rather Yes, -1: Rather No and -2: Absolutely No.

The meaning of the participants' free commentaries was analysed and the commentaries were split in five categories as follows:

(i) Comments describing "Signs actually used" by the other vehicle to imply motion intention
(ii) Comments describing "Signs searched for" to anticipate motion intention
(iii) Comments referring to trust towards the other driver ("Trust human driver")
(iv) Comments from drivers in Setup 2 referring to trust towards the AV "Trust AV no eHMI"
(v) Comments from drivers in Setup 1 referring to trust towards the AV "Trust AV with eHMI"

A list of the "signs" extracted from the commentaries with examples of comments is shown in Table 2.

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Table 2: “Signs actually used”, “Signs searched for”, and comment examples

User ID	Example commentary	Sign	Category
Setup 2 [17]	[…] while [the car] was **decelerating**, I was sure that it would stop and let me to pass.	– Deceleration (CV / AV)	***Signs actually used***
Setup 2 [07]	I was looking at the **wheels** to see when they would stop.	– Wheels (CV / AV)	
Setup 2 [10]	When the other vehicle was **completely stopped**, yielding was clear.	– Stopped (CV / AV)	
Setup 2 [03]	A **full stop** was the signal for me to trust and I was **waiting a second** to look what happens.	– Stopped + Waiting (CV / AV)	
Setup 2 [19]	I was sure that they would give me way when they turned on the **indicators** and I passed when they were **completely stopped**.	– Turn signal + Stopped (CV / AV)	
Setup 1 [09]	To pass the autonomous vehicle I was only looking at the **lights**	– LED stripe (AV)	
Setup 1 [15]	In the autonomous, I was sure for the **lights**. In the conventional vehicle I understood the driver's intention only because he **stopped.**	– Stopped (CV) – LED stripe (AV)	
Setup 1 [08]	I turned when I realized that the car was **not making a move** indicating he was going to turn. Encounter with autonomous didn't bother me due to the knowledge of the meaning of **lights**	– Stopped + Waiting (CV) – LED stripe (AV)	
Setup 1 [13]	In both cars, I focused mainly on the **vehicle motion** and the **lights** (turning indicator for conventional / LED stripes for autonomous).	– Deceleration + Turn signal (CV) – Deceleration + LED stripe (AV)	
Setup 2 [06]	In both cars I made a **gesture** to signal that I was giving way to them. The longer I **waited**, the more I was certain that they wouldn’t move.	– Gesture + Waiting (CV / AV)	***Signs searched for***
Setup 1 [03]	It seemed unnatural to me, if I didn't see a yielding **gesture** by the other driver	– Gesture (CV / AV)	

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The commentaries that related to trust were split in three levels according to whether they indicated: Trust, Indifference or Mistrust. Example comments and their indications are shown in Table 3, Table 4, and Table 5.

Table 3: "Trust human driver" indications and comment examples

User ID	Example commentary	Trust level	Category
Setup 2 [10]	In real conditions you can **better understand** whether the other driver will yield or not.	Trust	***Trust human driver***
Setup 1 [06]	A human-driver **transmits** an extra set of signals while looking at his face/eyes.	Trust	
Setup 2 [16]	I **didn't pay attention** if there was a driver or not. I was waiting for the other car to completely stop, before to start.	Indifference	
Setup 1 [19]	My attention was focused on the car, not on the drivers	Indifference	
Setup 2 [05]	It **doesn't matter the driver** of the other vehicle even if he makes a motion to me for passing.	Mistrust	
Setup 2 [06]	In both cases, I paid attention to turning indicator and vehicle full stop, as I also do it in real traffic due to **mistrust** of other drivers.	Mistrust	
Setup 1 [11]	When other driver gives way to me, I am **on my guard** during the maneuver	Mistrust	
Setup 2 {03]	I waited a while to look what happens	Mistrust	

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Table 4: "Trust AV no eHMI" indications and comment examples

User ID	Example commentary	Trust level	Category
Setup 2 [13]	With the autonomous vehicle, I was **sure that it would stop.**	Trust	***Trust AV no eHMI***
Setup 2 [01]	I **expect** from a robot to give way to me. Since the robot is stopped, I **expect** that it will remain stopped.	Trust	
Setup 2 [18]	There was **no difference** between the conventional and the autonomous car	Indifference	
Setup 2 [11]	With the autonomous vehicle I was **more careful/cautious**, so I **waited for longer** time.	Mistrust	
Setup 2 [06]	In both scenarios I was **not sure** that the other vehicle will not move.	Mistrust	

Table 5: "Trust AV with eHMI" indications and comment examples

User ID	Example commentary	Trust level	Category
Setup 1 [11]	With the autonomous vehicle, it was **perfectly clear** that I had been given priority.	Trust	***Trust AV with eHMI***
Setup 1 [13]	[With repetition], I felt **more confident** with the yielding signal by the AV than the driver.	Trust	
Setup 1 [18]	In the AV I noticed the lights because you told me, otherwise my reaction would be **the same**.	Indifference	
Setup 1 [06]	Although I knew that flashing lights meant yielding, I didn't maneuver […]	Mistrust	

3.3 Results

The responses to the Likert-scale questions are shown below (Table 6 and Table 7). Responses ranged from -2 (absolutely no) to +2 (Definitely yes). Drivers responses show that they turned slightly more

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slowly in front of the AV without eHMI (mean value = 0.04) compared to the other conditions (mean values were -0.35, -0.44 and -0.22). Yielding seemed rather realistic in all cases, both for the AV and the manual vehicle. The drivers responded that they had a better understanding of the intention of the AV with the eHMI, than the intention of the human driver (M = 0.52 vs M = 0), while their level of understanding was similar for the AV without and without eHMI (M = 0.17 in both cases). The drivers felt relatively safe in all conditions, with slightly higher values for the manual vehicle than the AV (M = 1.4 vs M = 1.12 in Setup 1 and M = 1.43 vs M = 1.17 in Setup 2).

Table 6: Subjective responses to the Likert-scale questions

		I waited more than usual to turn	Yielding seemed realistic to me	I understood the other vehicle's intention before it stopped	I felt safe before and while turning
Setup 1	"Manual"	-0.36	0.4	0	1.4
	"AV with eHMI"	-0.44	0.76	0.52	1.12
Setup 2	"Manual"	-0.22	0.78	0.17	1.43
	"AV no eHMI"	0.04	0.83	0.17	1.17

In both setups, the drivers rather trusted the AV slightly more than the human drivers (M = 0.52 vs M = 0.32 in Setup 1 and M = 0.61 vs M = 0.48 in Setup 2). They responded that the LED stripe made turning easier (M = 1.12 in the -2 to +2 scale). Drivers in Setup 2 who interacted with the AV without eHMI responded that they perhaps needed some indication from the AV (M = 0.17 in the -2 to +2 scale).

Table 7: Subjective responses to the Likert-scale questions

	The driver on the wheel made me feel safe	The AV's movement made me feel trust to the AV	The flashing yielding LED stripe made it easier for me to turn	I needed some yielding indication from the AV in order to decide
Setup 1	0.32	0.52	1.12	
Setup 2	0.48	0.61		0.17

The intention signs used or searched for by drivers, according to their commentaries, are presented in Table 8 and Table 9. As seen in Table 8, in Setup 2 drivers reported the same signs for both the manual

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vehicle and the AV. In Setup 1, drivers predominantly reported using the LED stripe. Very few commentaries reported searching for signs coming from the other human (Table 9).

Table 8: Number of reports of "Signs actually used"

Signs actually used	Setup 2		Setup 1	
	"Manual"	"AV no eHMI"	"Manual"	"AV with eHMI"
Stopped	12	11	5	2
Deceleration	6	4	6	3
Wheels	1	1	-	-
LED	n/a	n/a	n/a	9
Turn signal	3	1	1	0
Wait	3	3	2	0

Table 9: Number of reports of "Signs searched for"

Signs searched for	Setup 2		Setup 1	
	"Manual"	"AV no eHMI"	"Manual"	"AV with eHMI"
Gesture	1	1	1	-
Eye-contact	1	-	-	-

The number of comments per trust level is presented in Table 10. The distribution of trust level towards the other human driver is similar in both setups. In contrast, a clear difference can be seen between the two setups as regards trust towards the AV. Drivers in Setup 1 commented much more frequently that they feel trust towards the AV with the eHMI than in all other conditions (10 vs 3 trust related comments for the human driver in Setup 1; 3 comments for the AV without eHMI and 2 comments for the human driver in Setup 2).

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Table 10: Number of commentaries per trust level towards the human driver and the AV

Trust level	Trust towards the other human driver		Trust towards the AV	
	Setup 2	Setup 1	Setup 2	Setup 1
Trust	2	1	3	10
Indifference	13	11	16	3
Mistrust	4	3	1	1

3.4 Conclusions

The drivers' responses to the closed questions in this study indicate that the eHMI increased participants' comprehension of the AV's intention (average rating of 0.52 for the AV with eHMI vs 0.17 for the AV without eHMI; and average ratings of 0 and 0.17 for the human driver, depending on the experimental set up).

Even more, according to the drivers' free commentaries, the presence of eHMI increased the level of trust felt towards the AV, compared to both the AV without eHMI and the human driven vehicles.

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4. Threat assessment

In Chapters 2 and 3, we provided evaluations of the interACT communication solutions developed in WP4 of the project, looking at the effect of eHMIs and AV behaviours on traffic efficiency and road user perceptions. In Chapter 4, the focus moves to the evaluation of the interACT Safety Layer developed in WP3, providing software for threat assessment of traffic scenes based on a probabilistic prediction of other traffic participants.

4.1 Literature and background

Threat assessment is a crucial component of autonomous vehicles and helps to avoid collisions and to assess the criticality of a given traffic scenario (Lefévre, Vasquez, & Laugier, 2014). To provide high levels of safety, autonomous vehicles have to reliably determine whether a potential collision is near and whether the vehicle is able to avoid it. If the intended motion of the autonomous vehicle will (most likely) end in a collision, safety systems, such as the proposed safety layer in the interACT project, can eliminate or reduce the severity of the impact. It is important that safety systems only intervene if necessary. For instance, if the autonomous vehicle detects that no evasive trajectory exists anymore, at a certain point in time, the vehicle can already take countermeasures to avoid the safety-critical situation. Moreover, threat assessment can be used to determine optimal trajectories, with low criticality.

4.1.1 Detecting inevitable collisions

To ensure that safety systems intervene at the latest possible point in time, i.e., when collisions are unavoidable, it is often checked whether a collision-free motion from a finite set of possible evasive maneuvers exists (Brännström, Coelingh, & Sjöberg, 2010; Kaempchen, Schiele, & Dietmayer, 2009), (Kaempchen, Schiele, & Dietmayer, 2009). States of the vehicle in which no collision-free motion exists are known as *Inevitable Collision States* (ICS) (Fraichard & Asama, 2003). ICS are states in which the autonomous vehicle eventually collides regardless of what trajectory it follows. To guarantee that a collision is unavoidable, reachable sets can be used to check whether all feasible trajectories of the vehicle lead to a collision. The reachable set is the set of states reachable for the vehicle, subject to all admissible inputs. For instance, the work in Falcone, Ali, & Sjöberg (2011) uses backward reachable sets to analyze lane departure systems. The authors of Schmidt, Oechsle, & Branz, (2006) determine all reachable positions while ignoring the velocity domain, which results in overly large reachable regions. In Söntges & Althoff (2018), the authors compute an over-approximation of the reachable set of the

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vehicle, while accounting for position, velocity, and acceleration constraints. This over-approximation is used to check whether evasive trajectories exist in Söntges & Althoff (2015).

4.1.2 Time-To-Collision

Besides determining whether a collision is unavoidable, it is often helpful to further obtain the point in time until a collision occurs when continuing the intended motion of the vehicle. The Time-To-Collision (TTC) is defined as the time until a collision occurs with respect to a given intended motion of the autonomous vehicle and of each surrounding traffic participant (Hayward, 1972) (see Figure 13). Analyzing the worst-case of the TTC is investigated in Wachenfeld, Junietz, Wenzel, & Winner (2016) and Pek & Althoff (2018). To account for uncertainties, probabilistic versions of the TTC can be computed using stochastic predictions of motions (Berthelot, Tamke, Dang, & Breuel, 2012, Ward, Agamennoni, Worrall, Bender, & Nebot, 2015, Schreier, Willert, & Adamy, 2016).

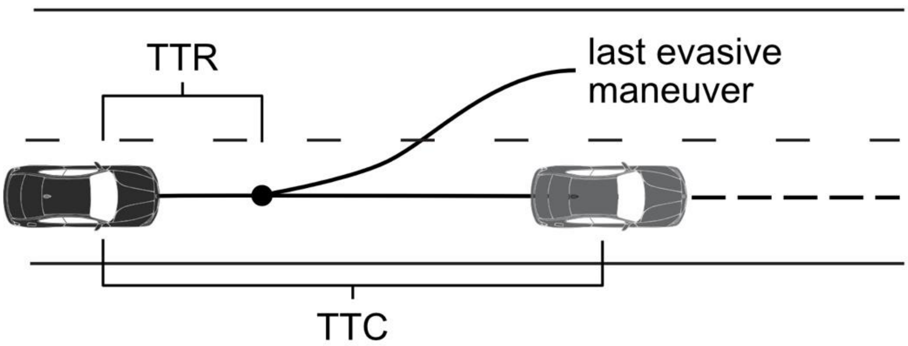

Figure 13: TTC and TTR in an example scenario.

4.1.3 Time until last evasive manoeuver can be executed

The TTC is not sufficient to determine if the autonomous vehicle is able to avoid a collision, since it does not account for possible evasive manoeuvres. For instance, a collision may occur in one second, but the vehicle should have executed a braking manoeuvre two seconds ago to avoid the collision. For that reason, the Time-To-React (TTR) has been introduced. The TTR corresponds to the remaining time along the intended motion until the autonomous vehicle can still execute a collision-free trajectory (Hillenbrand, J., Spieker, & Kroschel, 2006) (see Figure 13).

The TTR is often computed by considering sets of manoeuvres, e.g., braking or steering manoeuvres. For instance, TTR is defined using different sets of evasive manoeuvres through the maximum of the

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Time-To-Brake (TTB), Time-To-Steer (TTS), and Time-To-Kickdown (TTK) in Hillenbrand, Spieker, & Kroschel (2006). Time-based metrics are often generalized as Time-To-X (TTX). The TTX corresponds to the time until an action X still exists. Similar to the TTC, uncertainties can also be considered while computing the TTR by incorporating probabilistic collision avoidance systems (Althoff, Stursberg, & Buss, 2009; Eggert, 2014; Annell, Gratner, & Svensson, 2016).

4.2 Application to fail-safe trajectory planning

The safety layer developed in this project ensures that the autonomous vehicle does not cause collisions with other traffic participants (more details on the safety layer can be found in deliverable 3.2). Therefore, the safety layer verifies the intended motion of the autonomous vehicle, denoted as ego vehicle in the following, by planning fail-safe trajectories (see Figure 14). These fail-safe trajectories serve as back-up trajectories in case a safety-critical situation occurs and branch from the intended motion. To improve the comfort for passengers, fail-safe trajectories should start at the latest possible point in time along the intended motion. To determine this point, the safety layer computes the TTR.

Since fail-safe trajectory planning should not be limited to a certain type of manoeuvre (e.g., braking), the TTR cannot be exactly computed considering the large set of possible trajectories. Instead, under- and over-approximations are computed, using invariably safe sets (Pek & Althoff, 2018) and reachability analysis (Söntges, Koschi, & Althoff, 2018), respectively. Both methods to compute the TTR are evaluated and their impact on threat assessment analysed and compared to the threat assessment of humans in this study.

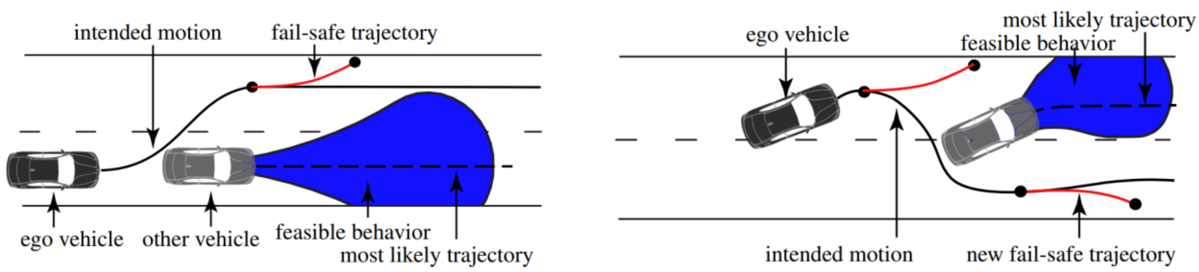

Figure 14: Principle of fail-safe trajectories (Pek, Koschi, & Althoff, 2019): While moving along the intended motion, the ego vehicle constantly plans fail-safe trajectories with ensure that it does not cause collisions with other traffic participants.

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4.3 Data utilized for evaluation

The developed threat assessment methods are evaluated in simulation. Therefore, different safety-critical scenarios from the CommonRoad benchmark suite are used (Althoff, Koschi, & Manzinger, 2017, see https://commonroad.in.tum.de/). These scenarios are modelled from real-world data (e.g., the NGSIM US101 dataset) or artificially created. Figure 15 illustrates an example scenario in which the ego vehicle (start position indicated with green circle) is required to turn left to arrive in the red goal region.

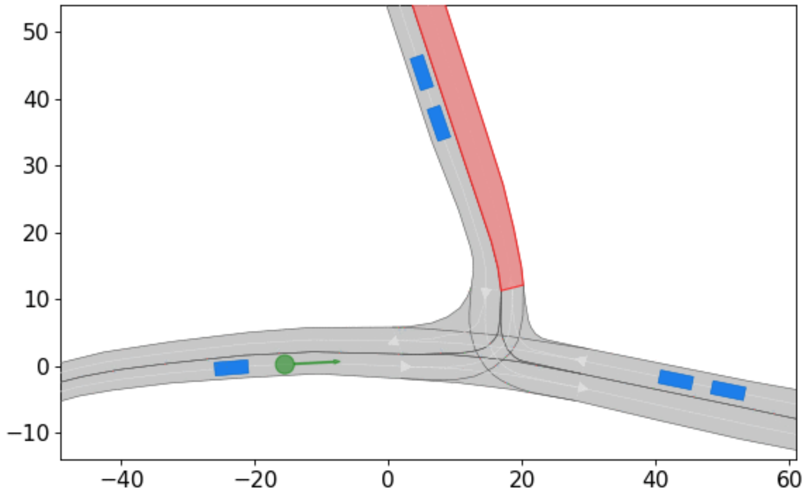

Figure 15: Visualization of the CommonRoad scenario ZAM_Tjunction-1_524_T-1:2018b: The ego vehicle starts at the initial position (denoted as a green circle) and has to reach the goal area (red region).

Since the threat assessment metrics should be investigated in highly safety-critical traffic situations, new scenarios are artificially synthesized for increased criticality (Klischat & Althoff, 2019). The scenario creation is done by computing the drivable area (i.e., the projection of the reachable set of the ego vehicle onto the position domain) for a given scenario, and iteratively shifting the positions of other traffic participants so that the driveable area is below a user-defined threshold. As a result, the size of the solution space of the ego vehicle (to plan motions) in the created scenario is decreased. Figure 16 illustrates this process for an example highway scenario. The driveable area (shown as a red area) is minimized in the optimised scenario. More details of the creation of safety-critical scenarios can also be found in Deliverable 3.2 (Markowski et al., 2019).

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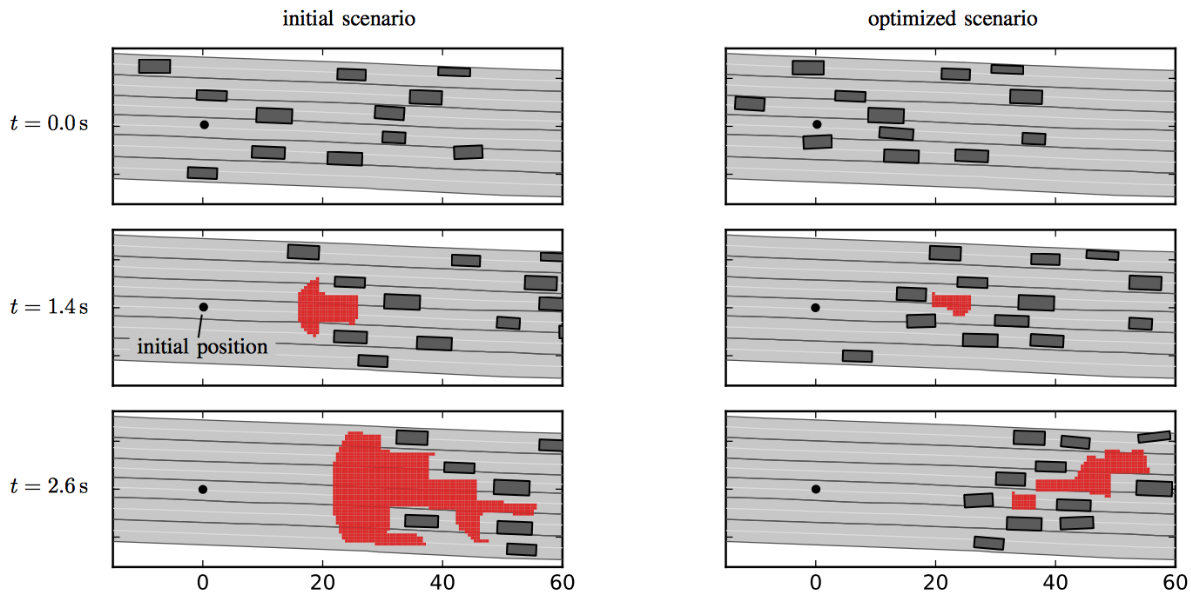

Figure 16: Creation of safety-critical scenarios (Klischat & Althoff, 2019): The initial scenario is optimized for higher criticality by shifting the position of obstacles such that the drivable area of the ego vehicle (red regions) becomes smaller.

4.4 Results of the threat assessment studies

4.4.1 Objective safety of proposed fail-safe trajectory approach

The proposed verification approach ensures that the autonomous vehicle is always able to avoid a collision with respect to all possible legal behaviours of other traffic participants, by executing fail-safe trajectories. These verifiable safe trajectories are planned continuously while the vehicle is moving along its intended motion plan and ensure that the vehicle remains within a safe state at all times. The approach has been validated with different (urban and highway) scenarios from the CommonRoad benchmark suite. Figure 17 and Figure 18 show excerpts from the conducted experiments for highway and pedestrian scenarios, respectively. Random simulations of legal behaviours of other traffic participants confirm the proposed safety benefits of fail-safe trajectories; in all simulations, the autonomous vehicle remains collision-free and safely comes to standstill.

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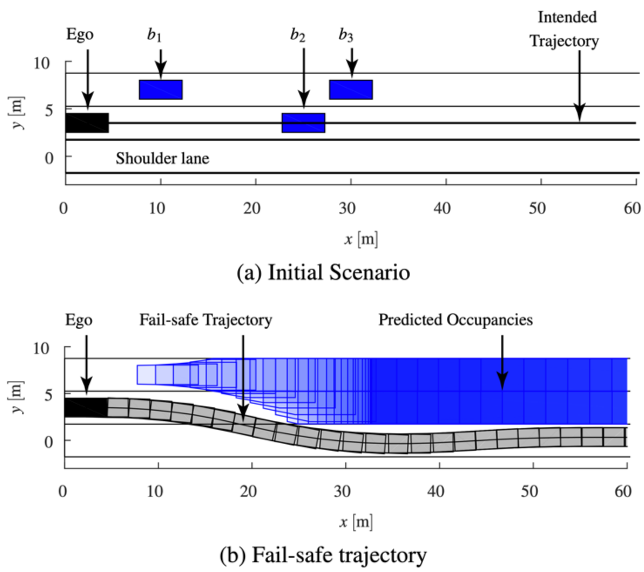

Figure 17: Fail-safe trajectory planning for the CommonRoad scenario ZAM_HW-1_1_S-1:2018b: The fail-safe trajectory lets the ego vehicle swerve to the adjacent shoulder lane.

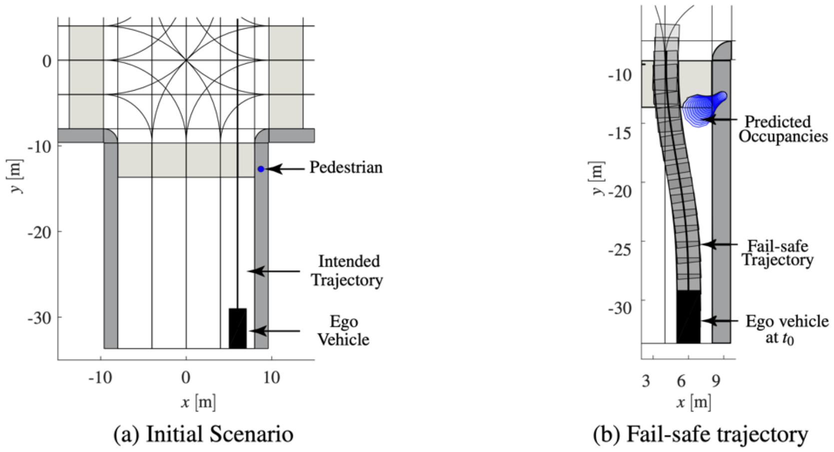

Figure 18: Fail-safe trajectory planning for the CommonRoad scenario ZAM_Intersect-1_1_S-1:2018b: The fail-safe trajectory lets the ego vehicle swerve around the pedestrian.

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4.4.2 Objective criticality of traffic scenario

To evaluate the (objective) criticality of traffic scenarios, the TTR is computed using over-approximated reachable sets and invariably safe sets in different traffic scenarios. Since the exact TTR usually cannot be precisely computed, the former method obtains an upper bound and the latter method a lower bound on the TTR. Figure 19 and Figure 20 show the results of TTR computation using over-approximated reachable sets. In this approach, the reachable set of the ego vehicle is computed for each state $x_t, t \in \{t_0, t_1, \dots, t_h\}$, along the intended motion for a predefined time horizon t_{reach}. As soon as the reachable set becomes empty during the computation for a state x_{t_i} (i.e., no collision-free trajectory exists), the TTR is determined as $t_* = t_i - t_0$. In the first scenario, the TTR is over-approximated as $t_* = 0.7s$, meaning that the scenario has less criticality, since the autonomous vehicle has multiple planning cycles (time step of $0.1s$) to determine a suitable evasive trajectory.

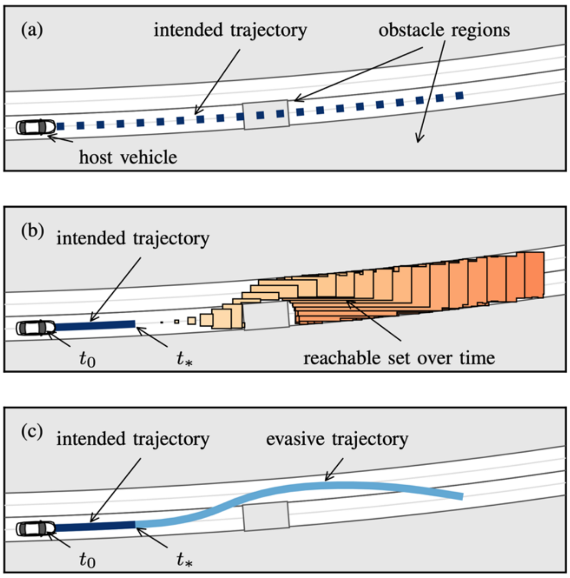

Figure 19: TTR (denoted as t_*=0.7s) computation using reachable sets for the CommonRoad scenario ZAM_Over-1_1:2018b.

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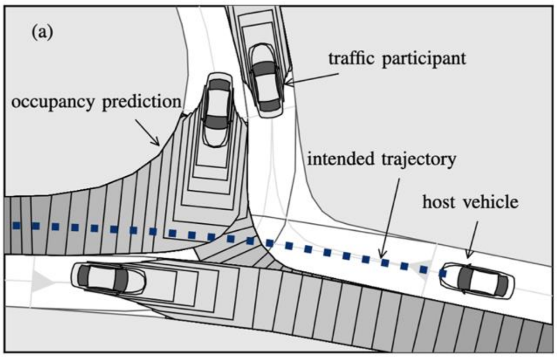

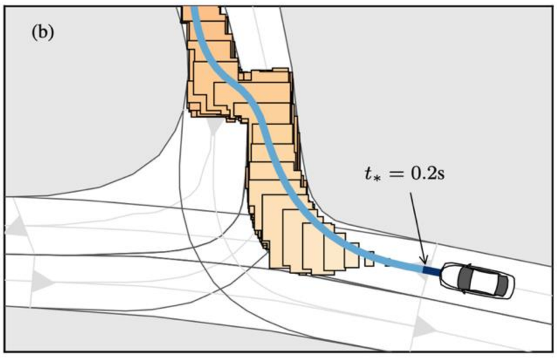

Figure 20: TTR (denoted as t*) computation for the CommonRoad scenario ZAM_Tjunction-1_524_T-1:2018b.

In contrast, the second scenario has a higher criticality. Here, the TTR is computed as $t_* = 0.2s$, since the autonomous vehicle is approaching the traffic participant that may either turn left or right. The criticality can also be seen from the computed evasive manoeuvre. The obtained manoeuvre is rather complex and planned near the physical limits of the vehicle. This result is confirmed when looking at the under-approximated TTR, which corresponds to $\underline{t}_* = 0.1s$. To compute the under-approximation, the invariably safe set for the ego vehicle in the scenario is computed. The lower bound of the TTR is then obtained by determining the point in time when the intended motion is not enclosed in the computed invariably safe set anymore. Figure 21 shows the fail-safe planning result for a scenario from the CommonRoad benchmark suite and Figure 22 the detailed planning results, including the TTR computation using invariably safe sets (Pek, 2020).

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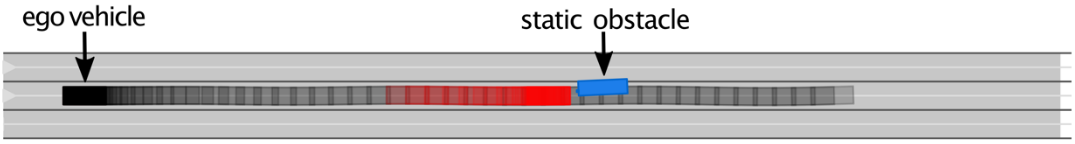

Figure 21: Fail-safe planning result for the CommonRoad scenario ZAM_Urban-2_1:2018b.

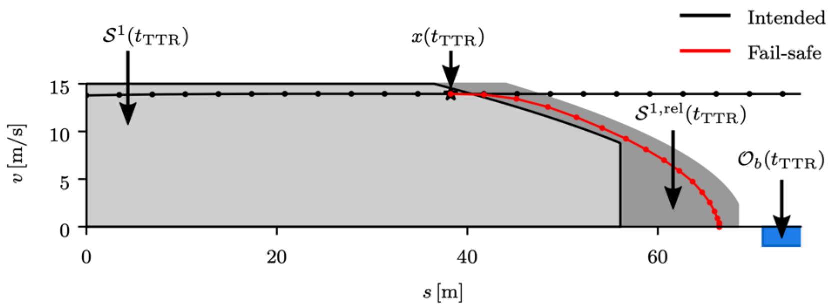

Figure 22: Computation of the Time-To-React using invariably safe sets (shown as grey regions).

4.4.3 Subjective criticality of traffic scenario

The computed TTR metrics in Sec. 4.4.2 are based on the set of possible evasive manoeuvres. Thus, the TTR is an objective measure whether the autonomous is still able to avoid collision with other traffic participants. Nevertheless, the presented metrics may not reflect the subjective threat assessment of human drivers. Situations that are rated differently by human drivers may thus result I in less comfort for passengers. To evaluate whether the proposed metrics reflect human threat assessment, a user study has been conducted (Baumann, 2019). In this study, 95 participants were asked to rate the criticality of 13 different scenarios on a numerical scale from 0% (not critical) to 100% (highly critical). Therefore, videos of the scenarios have been created and were shown to the participants. Figure 23 shows a screenshot of the last frame of an example scenario. In this scenario, the autonomous vehicle is quickly approaching a significantly slower preceding truck.

For all scenarios, the TTR is computed with the two methods above. The obtained times are scaled linearly in the interval [0,100] with different slopes. The resulting criticality values are compared to the human threat assessment in each scenario. Figure 24 shows the results of the average subjective criticality values and the objective criticality values for the best matching slope value. Based on the obtained results, it becomes apparent that the TTR does not always matches the human assessment of the traffic scenario. In fact, five of the scenarios are objectively more critical than the participants'

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ratings. In three scenarios, the subjective and objective criticalities are indistinguishable. In five scenarios, the participants rated the situation more critical than the objective rating.

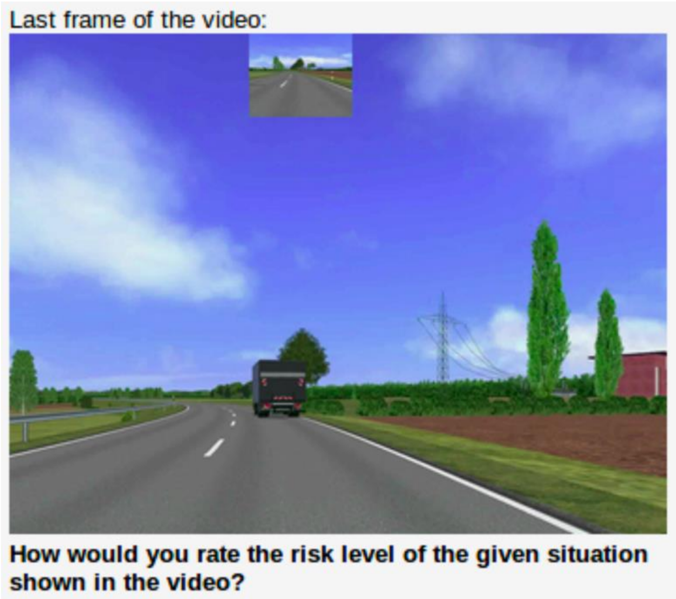

Figure 23: Example scenario of conducted user study.

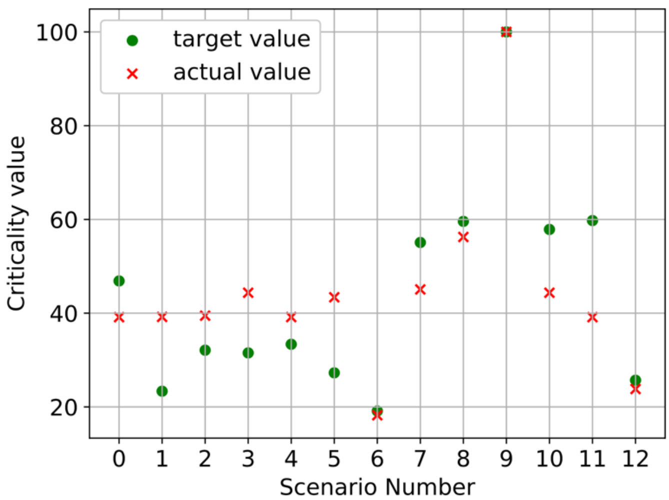

Figure 24: Comparison of the subjective (target value) and objective (actual value) criticality values.

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4.5 Conclusion

The proposed online verification technique plans fail-safe trajectories to ensure that autonomous vehicles never cause collisions when other traffic participants behave according to traffic rules. The proposed safety layer ensures safety in arbitrary traffic situations, since the technique assesses the safety of each traffic scenario on-the-fly during operation of the vehicle. As a result, it is expected that the number of traffic accidents will not increase with the introduction of autonomous vehicles that incorporate the developed safety layer and may also decrease with the adoption of autonomous vehicles over time. The conducted simulations validate this finding. Moreover, the developed threat assessment techniques allow autonomous vehicles to determine if a safety-critical situation arises and proactively take countermeasures. The developed metrics mainly reflect the complex threat assessment of human drivers which has been validated in a large user study with 95 participants. It is expected that the proposed safety layer will increase the comfort for passengers and the trust of humans in autonomous vehicles.

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5. Summary and final conclusion

In this Deliverable, a variety of methods and studies were used to evaluate the eHMI solutions (Weber et al., 2019) and the safety layer (Drakoulis et al., 2018; Markowski et al., 2019) developed in earlier interACT Work Packages.

Overall, the results suggest that the inclusion of the interACT eHMI solutions can lead to increases in pedestrian and AV efficiency, along with increases in perceived safety, comprehension and trust. The human interaction models and simulations described in Chapter 2 show that the inclusion of eHMI could lead to time savings of up to 1.5 s and 3 s respectively for the AV and pedestrian per interaction when yielding behaviour is optimised. These time savings can be achieved by the AV with a smaller magnitude of deceleration, compared to the situation without eHMI.

The questionnaire and free-response data described in Chapter 3 found that eHMI also seem to lead to an increase in perceived safety, a trend towards higher understanding of the AV intention, and greater levels of trust in the eHMI. However, drivers also indicated that when there is no eHMI available, the trajectories of AVs will be used to form judgements about intended behaviours.

Finally, the results of Chapter 4 show that the incorporation of the interACT safety layer means that the AV will not cause an accident, no matter how vulnerable road users are moving. In turn, we expect that the proposed safety layer will then increase the comfort and trust of humans in AVs. The evaluation of safety layer is validated based on different (urban and highway) scenarios from the CommonRoad benchmark suite (see https://commonroad.in.tum.de/) and therefore has taken the current road infrastructure into account.

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Designing cooperative interaction of automated vehicles with other road users in mixed traffic environments