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Deliverable 1.2

Perceived safety and predictability of human/AV interactions

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Deliverable 1.2 Perceived Safety and Predictability of Human/AV Interactions

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List of Associated Partners

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Note 1: The term Early-Stage Researcher (ESR) is used extensively in this document. The ESRs are PhD candidates funded by the SHAPE-IT project.

Note 2: This document has been submitted to the EC for acceptance as a deliverable in the SHAPE-IT project. If changes are requested by the EC, the document will be updated.

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Contents

Introduction

In the fast-evolving landscape of transportation, the integration of Automated Vehicles (AVs) holds immense promise for revolutionizing mobility and enhancing road safety. As we embark on this transformative journey, it is imperative that we investigate and understand the intricacies of the interactions between humans and AVs, because successful integration of AVs into the urban fabric hinges not only on their technical proficiency but also on human factors. Consequently, the fundamental premise of our exploration is that a thorough understanding of the perceived safety and predictability of AVs is of key importance.

Supporting the development of AVs that are perceived as safe requires the consideration and integration of different aspects and perspectives on predictability that are highly related to each other. On the one hand, the drivers and passengers inside the vehicle must, at least in principle, be able to understand and predict the behaviour of the AV, because any unexpected behaviour would reduce their acceptance and trust—and consequently their willingness to adopt this technology. To achieve this goal, the AV's behaviour (and, ideally, its underlying goals and plans) must be made transparent to the humans inside the vehicle. On the other hand, the behaviour— specifically the movement—of an AV depends in part on the movements of the surrounding humans. In highly dynamic, social environments such as urban traffic, the ability of AVs to predict the movement of vulnerable road users (VRUs) is therefore paramount. The AVs' proactive and anticipatory responses can enhance overall road safety and contribute to their efficient, harmonious integration into shared urban environments. Thus, to some degree, these prediction functions must be transparent to the humans inside the AV, to facilitate predictability of AV behaviour (so that the humans in the AVs know what to expect) and to ensure that they experience an appropriate level of perceived safety.

Although this deliverable is in SHAPE-IT work package 1 ("Safe and transparent interactions between AVs and humans inside the AVs"), we have included both in-AV and outside-AV perspectives. This decision was motivated by the interdependence of these two perspectives and the multi-disciplinary emphasis of SHAPE-IT. Essentially, we addressed the multifaceted challenges presented by the predictability of human movement behaviour from both inside and outside the AV. Our empirical results shed light on many nuances of the factors that influence the subjective sense of safety experienced by individuals as they interact with AVs. Our approaches included subjective evaluations, neuroergonomics methodologies, and modelling approaches—as well as revelations about the degree to which AV-VRU interactions can be accurately predicted.

In the three chapters of this deliverable, we will explain our findings, which reveal the complex tapestry of human-AV interactions. Results from empirical and modelling research on the perceived safety of AVs and the predictability of human-AV interactions will be presented. By revealing the interwoven threads of perceived safety and predictability, we hope to contribute not only to academic discourse but also to the practical implementation of AV technologies. Our endeavour aligns seamlessly with the European Union's commitment to fostering innovation that prioritizes human-centric design, thereby ensuring that future mobility is not just automated but, more importantly, safe, and predictable for all.

1. Perceived safety

1.1. Definition

Risk, an essential determinant of perceived safety, is defined as *"the combination of the probability of occurrence of harm and the severity of that harm conditions*" (ISO 26262-1). A certain level of risk always exists, but some risks are "*judged to be unacceptable in a certain context according to valid societal moral concepts*" (ISO 26262-1).

Based on the definition of risk, functional safety can be objectively defined as the *"absence of unreasonable risk due to hazards caused by malfunctioning behaviour of electrical and/or electronic systems"* (ISO 26262-1). This definition gives an accurate and precise scope for risk and functional safety that has been broadly applied in many studies. In the context of automated driving systems, the definition implies zero accidents caused by systems failures in automobiles.

Perceived safety and *perceived risk* are complementary psychological concepts describing the subjective evaluation of safety by users of automated driving systems and other road users interacting with automated vehicles (AVs; Griffin et al., 2020; Kolekar et al., 2020). Perceived risk can differ from actual operational risk (Griffin et al., 2020; Kolekar et al., 2020). Many researchers have studied perceived safety, but only those who tried to clarify its theoretical aspects offered a definition. Here are three such definitions: Mösinger (2017) defined perceived safety as not actual safety but the feeling of safety people have when they trust their welfare to a machine whose workings are not transparent; Osswald et al. (2012) defined it as the degree to which an individual believes that using AVs will not harm their well-being; and lastly Xu et al. (2018) defined it as an environment in which drivers and passengers can feel relaxed, safe, and comfortable while driving. These definitions describe a state of high perceived safety: users are not worried about injury and feel relaxed and comfortable. In contrast, if the perceived safety is low, users are worried and feel uneasy about using the automation.

1.2. Measurement of perceived safety

Most of the existing studies evaluate perceived safety in a specific scenario. The lack of actual perceived-safety data from occupants in many specific driving scenarios is a significant knowledge gap. Therefore, measurement methods that are applicable to and comparable over many different driving scenarios are of great importance in evaluating the perceived safety of occupants.

A questionnaire is the most common way to measure perceived safety in most studies because it is convenient and non-intrusive (Choi & Ji, 2015; Kraus et al., 2020; Nordhoff et al., 2020). Furthermore, their crucial advantage is that self-reported ratings from occupants are reliable (Wei, Bolton, & Humphrey, 2019). However, this kind of measurement focuses on recording the general views of those participants based on their own experience. To obtain more specific results, other researchers asked the participants to fill out the questionnaire after a particular experience with driving automation, improving the reliability of the results (Xu et al., 2018; Zoellick et al., 2019; He et al., 2022). There are other drawbacks to questionnaires, such as it being inherent problematic to get responses as a time-series (e.g., in an experiment) and a heavy memory load for the participants.

Continuous measurement devices, as variants of questionnaires, address these drawbacks. Researchers have used handset controls (Rossner & Bullinger, 2019), sliders (Saffarian et al., 2012), pressure sensors (He et al., 2022), rotary bars (Cleij et al., 2019), and angle sensors (Kolekar et al., 2020) to collect ratings of perceived safety or trust from participants. After ensuring the reliability and validity of the measures obtained with these devices, they can provide continuous data for analysis and modelling; at the same time, they can reduce the participants' memory load. In one application, He et al. (2022) proved that the peak of continuous ratings from a pressure sensor is highly correlated with the oral rating of perceived risk.

In addition to subjective ratings, surrogate measures such as physiological and behaviour indicators are also considered to reflect participants' perceived safety (Beggiato et al., 2019; Tenhundfeld et al., 2019; Wang & Akar, 2019). As with continuous measurement devices, participants do not need to memorise the scenario or think about giving a rating during automated driving, resulting in a lower mental workload. However, additional devices and sensors must be attached to participants' bodies, which is likely to sharply reduce participants' willingness to join the experiment. Most importantly, these indicators are simultaneously influenced by factors other than perceived safety, such as current driving task and steering behaviour, which makes data analysis more complex.

Surrogate metrics of safety (SMoS) can also be used to measure perceived safety. Examples include minimum time to collision (TTC), inverse time to collision (iTTC) (Kiefer et al., 2005), the potential index for collision with urgent deceleration (PICUD) (Van Beinum et al., 2016), and Driving Risk field (Mullakkal-babu et al., 2020). Although these metrics have been proven effective in measuring actual road safety, whether they capture perceived safety adequately remains largely unknown. However, appropriate experiments can be designed to establish the connections between SMoS and perceived safety.

1.3. Computation of perceived safety

A few studies are integrating perceived safety into driving automation design in various ways, such as in decisions about control transitions in full-range Adaptive Cruise Control (Varotto et al., 2018), collision warning system design (Kiefer et al., 2005, 2006), perceived-safety calculations in roundabout scenarios (Wang et al., 2006), perceived-safety calculations for tram drivers (Tzouras et al., 2020), and a driver's belief model about the probability of an event occurring (Kolekar et al., 2020). This research uses risk allostasis theory, driver risk field, regression model, and some SMoS to build the computational models. These models can calculate the current perceived safety of the occupants dynamically and can probably be used to control the vehicle's behaviour in order to maintain a low perceived risk. As such, the models can be considered dynamic. However, most of them are limited to specific scenarios and levels of automation.

1.4. Overview of results

The work of ESR12 is the study of perceived safety, its relation to trust and acceptance in driving automation, and its enhancement. Firstly, the factors influencing perceived safety were determined with a simulator experiment. In a second simulator experiment, several user interfaces (UIs) were tested for their influence on perceived safety, leading to recommendations for UI design to enhance perceived safety and trust. Finally, some efforts were made to build a computational model of perceived risk to estimate human drivers' perceived risk in real-time driving. This model also explains the mechanism of human drivers' risk perception.

The first experiment simulated 18 merging events with different merging distances and braking intensities on a 2-lane highway. Figure 1 shows an example of the simulated events. The participants were asked to monitor the scenario as fall-back-ready drivers in a vehicle with SAE Level 2 driving automation. During the drive, they used a pressure sensor to continuously give a perceived-risk rating from 0-10; these ratings constitute the continuous perceived-risk data. After each event, the participants were also asked to give a verbal rating from 0-10 of the previous event's perceived risk, which constitutes the discrete event-based perceived-risk data. The corresponding kinematic data (e.g., position, speed, and acceleration of the subject vehicle and neighbouring vehicles) were also collected.

A perceived-risk regression model shows that the motion relative to neighbouring road users accounts for most of the variation in perceived risk. Our models show modest effects of personal characteristics: experienced drivers are less sensitive to risk and trust automation more, while female participants reported higher perceived risk than males. However, perceived risk and trust are highly correlated and have similar determinants. Continuous perceived risk accurately reflects participants' verbal post-event rating of perceived risk, brakes are an effective indicator of high perceived risk and low trust, and pupil diameter correlates with the perceived risk in the most critical events. The events increased heart rate, but we found no correlation with event criticality.

Figure 1 *Video stream of a simulated merging event which included challenging braking*

In the second simulator experiment, five different interfaces (see the example in Figure 2) were designed with different information types and modalities. The simulation scenario was the same as in the first experiment above. The results indicate that the auditory modality providing manoeuvre information can help human drivers understand automation, contributing to enhancing perceived safety and trust.

Figure 2 *Interior of DAVSi driving simulator with designed user interfaces*

The data collected from the two simulator experiments were used to build and validate a new computational perceived-risk model, based on the potential collision avoidance difficulty (PCAD) for drivers of SAE Level 2 AVs. The perceived risk of the new model is visualised in Figure 3. The model performs well in terms of computation accuracy and detection rate, and fits the tendency of human drivers' perceived risk quite well.

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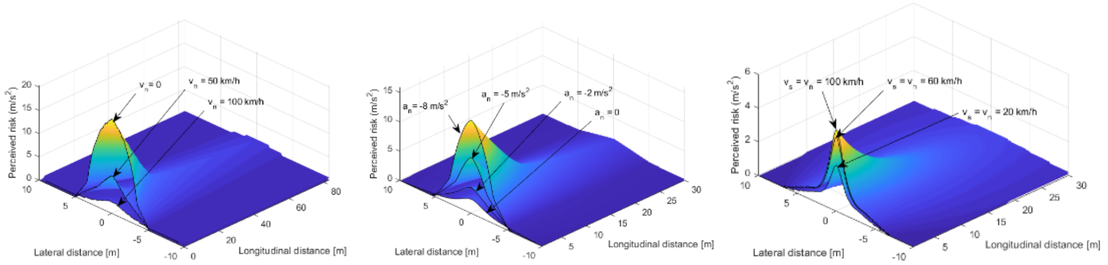

(a) (b) (c)

Figure 3 *Perceived-risk visualisation: The ego vehicle has (a) different velocities relative to the leading vehicle; (b) different accelerations; (c) different ego velocities*

1.5. Contribution and implications

The exploration of perceived safety in automated driving systems, as detailed in this research, has important implications for various fields and makes the following significant contributions:

1. Understanding Human Interaction with Automation: This work provides insights into humans' perceived safety regarding technology, vital for the design and acceptance of AVs.

2. Innovative Measurement Techniques: By introducing novel measurement devices and methodologies, the research paves the way for more accurate, real-time evaluations of perceived safety, enhancing data reliability.

3. Integration with Design and Control: The development of dynamic models which can be integrated into driving automation design represents a step towards creating vehicles that adapt to human perceptions. This advance has implications for enhancing user experience and could be key to the widespread adoption of AVs.

4. Enhancing Trust and Acceptance: Through experiments and interface designs, the research identifies ways to enhance perceived safety and trust in automated driving. These findings have direct implications for automotive manufacturers aiming to build user-friendly systems.

5. Policy and Regulation Considerations: The clear definitions and standards provided contribute to a framework that can guide regulations and policies, ensuring the safety and acceptability of automated driving systems.

In conclusion, the contributions of this research extend beyond the technical domain, influencing the way we understand, design, regulate, and interact with automated driving systems. It lays a foundation for a human-centric approach to automation, aligning with human perceptions and values.

1.6. Overview of published results on the topic

He, X., Stapel, J., Wang, M., & Happee, R. (2022). Modelling perceived risk and trust in driving automation reacting to merging and braking vehicles. Transportation Research Part F: Traffic Psychology and Behaviour, 86(July 2021), 178–195. https://doi.org/10.1016/j.trf.2022.02.016

Lu, C., He, X., Lint, H. Van, Tu, H., Happee, R., & Wang, M. (2021). Performance evaluation of surrogate measures of safety with naturalistic driving data. Accident Analysis and Prevention, 162(August), 106403. https://doi.org/10.1016/j.aap.2021.106403

Mullakkal-Babu, F. A., Wang, M., He, X., van Arem, B., & Happee, R. (2020). Probabilistic field approach for motorway driving risk assessment. Transportation Research Part C: Emerging Technologies, 118(July), 102716. https://doi.org/10.1016/j.trc.2020.102716

Nordhoff, S., Stapel, J., Xiaolin He, Gentner, A., & Happee, R. (2021). Perceived safety and trust in SAE Level 2 partially automated cars : Results from an online questionnaire. 1–21. https://doi.org/10.1371/journal.pone.0260953

2. Predictability in Human-Vehicle Interactions

2.1. Definition of predictability

Srivastava and Sarrafzadeh (2002) define predictability as *“the quantified form of accuracy”,* while the English dictionary defines it as *“the quality of being regarded as likely to happen, as behaviour or an event*” (Dictionary.com, 2023). In the field of human-computer interaction, predictability means the *“support for the user to determine the effect of future action based on past interaction history”* (Sandamal, 2020). Therefore, we assume that predictability is multifaceted, and we must understand the context in which the term is used in order to define it. In this text, we define predictability as *the property of a system or a situation which allows humans or automated systems to determine the future behaviour of other humans or automated systems.*

2.2. The importance of predictability in automated driving

Predictability is vital to decision-making in many fields, including transport (Chand, 2021). It is a crucial concept in automated driving. To ensure safety in mixed traffic, AVs should be predictable from both the inside and outside perspectives.

From the inside perspective, AV behaviour should be predictable for the operator. The growing awareness of the importance of predictability enhances the shift from unexpected take-over situations to HMI design for predictable transitions (Hecht et al., 2020). Predictable behaviour of the AV can lead to reduced reaction times and improved safety for automated driving (Hou, 2021). Predictability is also a key factor contributing to the perceived safety of passengers (Nordhoff et al., 2020).

From the outside perspective, we must consider two areas where predictability is necessary. First, the movements of AVs may be less familiar and therefore less predictable for other road users than the movements of manually-driven vehicles (Surden & Williams, 2016). Therefore, we should try to design predictable AV behaviour to increase mixed traffic safety. Second, the environments in which AVs operate are diverse and can change rapidly (Ito, 2019). Therefore, AV systems must successfully understand and predict the behaviour of other road users in a variety of situations (Dong & Dolan, 2018).

2.3. Predictability during the control transitions

Automated driving places different demands on drivers compared to manual driving. When driving manually (Level 0 automation), drivers control all aspects of the vehicle and must monitor their surroundings. They must stay alert to events arising from any direction, integrate information from various senses, and subsequently create a unified perception of the world (Spence et al., 2020). Additionally, drivers are required to constantly update their perceptual-motor loop and stay calibrated to the vehicle's dynamics.

SAE Level 2 AVs can perform both longitudinal and lateral control of the vehicle, but require drivers to continuously supervise them and respond immediately to automation failures. Level 3 AV operators are allowed to divert their attention from driving to other activities (SAE, 2013) so they might not be paying attention to their surroundings before a take-over request (TOR). Therefore, it is crucial that highly automated vehicles recognise the limitations of the automation's environment perception and inform the driver of a possible control transition ahead of time (Dietmayer, 2016).

When TORs are more predictable, drivers may have more time to get back in the loop (Merat et al., 2014) and adjust to the vehicle dynamics (Mole et al., 2019). Drivers can understand the status and forecast future states while perceiving the complicated traffic environment. More time to react boosts situation awareness and facilitates decision-making, improving take-over behaviour (Endsley, 1995).

To increase predictability, future systems should provide continuous feedback on the automation states (Norman, 1990) and offer further assistance before the control transition (Vogelpohl, 2018). To avoid additional demands on the processing power of the drivers, the support feedback might be sent via the peripheral vision channel (Wickens, 2008). Drivers will have enough time to assess the current situation and get acclimated to the vehicle dynamics when the TOR is predictable, leading to a smooth transfer of control (Shahini et al., 2022).

2.4. The importance of preparing drivers for a control transition

Since SAE Level 3 AVs allow drivers to engage in non-driving-related activities, the drivers only need to respond to TORs when the AV reaches its operational boundary. The switch in attention, however, impacts cognitive processes. Drivers of AVs experience higher fatigue (Figalova et al., 2023a; Matthews et al., 2019) and tend to mind-wander (Galera et al., 2012; Baldwin et al., 2017). Fatigue impairs the ability to operate a vehicle safely (e.g., Markkula et al., 2017; Higgins et al., 2017). Subsequently, drivers' ability to stay alert is impaired (Bieg et al., 2020; Vogelpohl et al., 2019). Moreover, drivers' ability to incorporate environmental information might be jeopardised (Galera et al., 2012); they pay less attention to their environment (Figalova et al., 2023b).

Even though vehicle automation increases drivers' fatigue and reduces their attention, drivers will be occasionally requested to take over control of the vehicle in Level 3 driving. An improper response to a TOR might create a safety-critical situation. It is therefore crucial to design driver-vehicle interactions in a way that mitigate the safety risks originating from fatigue and inattention.

2.5. Increasing predictability of control transitions using visual reliability cues

As part of her PhD project, ESR1 conducted a driving-simulator experiment to evaluate the efficiency of a four-stage likelihood alarm system conveying the current level of reliability of drivers' performance via ambient lightning (Figalova et al., 2022). ESR6 supported in the preparation and planning of a pilot study for this experiment and by discussing different concepts of automation transparency with ESR1 and how they could be applied to such an likelihood alarm system. The ambient alarm system comprised an ambient light in the vehicle's

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cabin: a green, yellow, orange, or red-light cue was delivered via an LED strip mounted around the vehicle's windshield. This system communicates reliability information using the unoccupied peripheral vision channel to avoid a system that is either overly conservative and prone to errors or overly liberal, resulting in the cry-wolf effect (Zirk et al., 2020).

Figure 4 *The apparatus of the experiment*

Participants performed a non-driving secondary task while operating a simulated Level 3 SAE (2013) vehicle. There were four trials, each around ten minutes long. They experienced ten TORs in total, each of which required drivers to disengage from the secondary task, understand the current traffic situation, deactivate the automation, perform the necessary manoeuvre (overtake the slow lead vehicle), re-activate the automation, and return to the secondary task. A between-group design was implemented to compare one group of drivers equipped with the ambient alarm system and a second group of drivers who were not.

We measured longitudinal vehicle jerk as an indicator of aggressive driving style (Feng et al., 2017). The self-reported mental workload was assed using the DALI questionnaire (Pauzié, 2008), and electroencephalography (EEG) measured brain activity in order to obtain psychophysiological indices of mental workload. Based on reports by other EEG researchers, we focused on the power in the theta (4-8 Hz) and alpha (8-13 Hz) frequency ranges, as changes in these are often referred to in the context of mental workload (Lohani et al., 2019).

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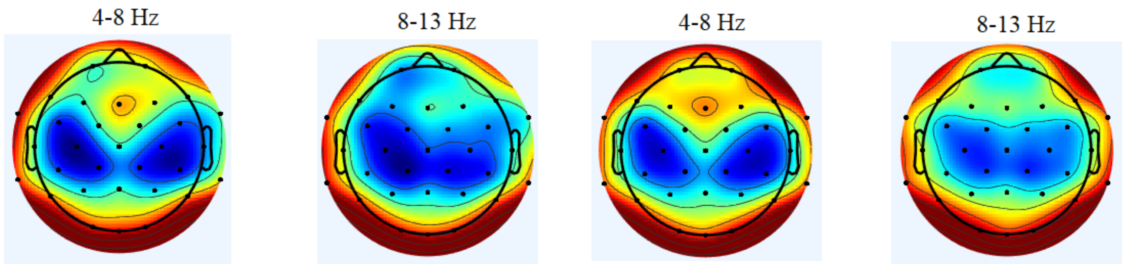
According to the driving performance data, in the first half of the experiment, drivers who had ambient light responded comparably to those who didn't. However, in the second half of the experiment, the drivers without ambient light exhibited an increase in vehicle jerk, while the drivers with ambient light exhibited no difference, or even a decrease. This result implies that individuals in the latter group performed better: they appeared to have greater control of the vehicle and better take-over performance, since their driving style was calmer and more predictable.

The increased mental workload was not a factor in the improved driving performance. Both groups perceived the same levels of mental workload, according to self-report and psychophysiological measures. Our findings imply that the task was equally difficult for all drivers regardless of ambient light; the ambient light provides information without adding to the cognitive load. Similar conclusions were reached by other researchers of ambient displays. The displays appear to help drivers deal with TORs and lane changes, as well as helping them manage their vehicle speed.



(a) Drivers without the ambient light (b) Drivers with the ambient light

Figure 5 *The theta (4-8 Hz) and alpha (8-13 Hz) power over the four consecutive trials. No significant differences in oscillatory brain activity were found for any of the trials.*

The four stages of the ambient light were acceptable and pleasant, according to participant reports and remarks. Moreover, participants often reported that they perceived the four stages rather as only two (green and yellow as less critical, orange and red as more critical), creating a sort of conservative binary alarm system. Based on prior literature, this effect was predicted We advise utilising the four-stage likelihood setting in reliability communication. The four stages allow a fine-grained communication and better user experience compared to binary systems while keeping their efficiency, safety, and performance of a two-stage alarm.

Overall, we developed and tested a new, four-stage likelihood ambient alarm system conveying the current reliability of the automated system. Such ambient alarm system setting has, to the best of our knowledge, not been studied before. Moreover, we successfully applied a novel neuroergonomic approach to evaluate our results in a driving-experiment study. The technical knowledge developed during this experiment helped us design further experiments employing EEG in the context of automated driving.

2.6. Contribution and implications

The ability to predict human-AV interactions has major safety implications. Our results contribute to the state of the art by presenting new empirical evidence of the cognitive processes during automated driving. The results suggest that drivers of AVs experience higher levels of fatigue compared to drivers of manual vehicles (Figalova et al., 2023a) and that they allocate fewer attentional resources to processing environmental information (Figalova et al., 20223b). It is therefore crucial to design AVs which consider drivers' fatigue and inattention, especially during extended periods of automated driving.

Moreover, we developed and tested an ambient lighting system which helps drivers perform better during the transition of control. This finding can be further elaborated on in the research domain (e.g., by investigating the best possible hardware and colour setting of the ambient lightning), as well as in the design domain (by implementing our findings in the design of future in-vehicle environments).

2.7. Overview of published results on the topic

Figalová, N., Chuang, L. L., Pichen, J., Baumann, M., & Pollatos, O. (2022). Ambient light conveying reliability improves drivers' take-over performance without increasing mental workload. *Multimodal Technologies and Interaction*, *6*(9), 73. https://doi.org/10.3390/mti6090073

Figalová, N., Bieg, H. J., Schulz, M., Pichen, J., Baumann, M., Chuang, L. L., & Pollatos, O. (2023a). Fatigue and mental underload further pronounced in L3 conditionally automated driving: Results from an EEG experiment on a test track. In *Companion Proceedings of the 28th International Conference on Intelligent User Interfaces* (pp. 64-67).

Figalová, N., Bieg, H. J., Reiser, J. E., Liu, Y. C., Baumann, M., Chuang, L., & Pollatos, O. (2023b). From Driver to Supervisor: Comparing Cognitive Load and EEG-based Attention Allocation across Automation Levels. *arXiv preprint arXiv:2306.08477*.

3. Predicting Interactions

3.1. Definition

We focus on the interaction in the road traffic domain in this project. Markkula et al. (2020) provided a conceptual framework for understanding interactive behaviour in human and road traffic, defining interaction as a situation where the behaviour of at least two road users is influenced by the possibility of occupying the same space simultaneously. Lehsing et al. (2016) focused on social interaction in traffic, and defined “interaction” as a goal-oriented, mutual process of behavioural adaptation by individuals through verbal and non-verbal communication. Rasouli and Tsotsos (2019) provided a comprehensive review of pedestrian behaviour considering both pedestrian-driver interactions and pedestrian-autonomous vehicles interactions, and stated that it is crucial to communicate and understand other road users’ intentions. Interaction is important for the understanding and prediction of the behaviour of road users.

3.2. Background and motivation

Driving safety is crucial. According to World Health Organization (WHO, 2018), every year, about 1.3 million people across the globe are killed by traffic crashes on the road; 310,000 are pedestrians, accounting for about 23% of all traffic deaths. This is an unacceptably high number that we need to reduce.

The vehicle automation industry has made many efforts to use technology to facilitate driving and improve driving safety. However, many risk factors are still causing road accidents; one of the main factors is human error (Rumar, 1999). Prediction technologies can provide information about vulnerable road users in advance, to reduce the cognitive load of the driver and provide more reaction time for the driving system (Zhang, 2022). A safe, intelligent vehicle must be able to use this technology to perceive and predict the behaviour of other road users around it.

Pedestrians are among the most vulnerable road users, and they need protection. Research shows that most pedestrian-vehicle collisions happen when pedestrians cross the road (Do et al., 2014), because in this situation they tend to interact with vehicles and other road users. By understanding these interactions, we can better predict the behaviour of pedestrians and reduce the risk of collisions (Zhang, 2022, Zhang and Berger, 2023). For AVs, predicting pedestrian behaviour is crucial for ensuring road safety.

Overall, the ability to understand and predict interactions between pedestrians and vehicles or AVs is vital for predicting the behaviour of pedestrians, providing more information for AVs and aiding self-driving (Zhang and Berger, 2023). Further, an AV whose behaviour is based on predicting the behaviour of other road users might itself be more predictable to drivers, and could therefore increase their perceived safety.

3.3. Methods for analysing and predicting the interaction

The interactions between pedestrians and AVs are relatively complicated (Zhang and Berger, 2023). In real-world traffic, various factors can influence the interaction. These factors include the behaviour and characteristics of the pedestrians such as their posture, heading direction, age, gender, and even their personalities (Zhang et al., 2023a), and the status of the vehicles such as their speed, acceleration, direction, or size (Zhang and Berger, 2023). The vehicle's behaviour can also influence the interaction if the vehicle is a human-driven car (Zhang et al., 2023a). In addition, the environment, which includes factors such as the road's condition (width, number of lanes), traffic signals, and traffic signs, can also influence the interaction.

Researchers have tried various methods to analyse and predict the interactions. For example, Rasouli et al. (Rasouli et al., 2019) reviewed existing studies on AV-pedestrian interaction. They identified two types of interaction studies. The first looks at how the vehicle communicates with pedestrians. The second seeks to understand the pedestrians' intentions. Our research, the second type, mainly focused on understanding and predicting pedestrians' intentions.

As we highlighted, many factors influence a pedestrian's behaviour and interactions. Due to this complexity, the conventional method of analysis cannot consistently and precisely anticipate pedestrian behaviour. Fortunately, artificial intelligence tools can handle the training and analyse pedestrian interactions (Zhang et al., 2023a). We used artificial intelligence techniques to identify the interactions between pedestrians and vehicles and understand pedestrian behaviour patterns. We modelled the interactions of pedestrians and evaluated the techniques' predictions of pedestrian behaviour, including the pedestrians' trajectories and crossing actions.

To predict the future trajectories of pedestrians, prediction models were built that consider the pedestrian-vehicle and pedestrian-AV interactions. We used the following two measures to report prediction errors and assess model performance (Alahi et al., 2016):

- **The Average Displacement Error** (ADE): the average distance gap between ground truth and prediction trajectories over all predicted time steps.
- **The Final Displacement Error** (FDE): the average distance gap between ground truth and prediction trajectories for the last predicted time step.

To predict pedestrians' crossing action, prediction models that consider the features of pedestrians and vehicles were built. Pedestrians' perceived risk can also be considered in the prediction. The following two measures can be used to evaluate the accuracy of the crossing decision prediction, by comparing the observed crossing decisions (who crossed first) after the communication between pedestrian and vehicle to the predictions.

- The accuracy is defined as: Accuracy = (TP + TN)/(P + N)
- The F1 score is defined as: F1 = 2TP/(2TP + FP + FN)

Where P is the number of positives, N is the number of negatives, TP denotes true positives, TN denotes true negatives, FP denotes false positives, and FN denotes false negatives.

The modelling of pedestrian-vehicle interactions can be indirectly assessed by evaluating the model's accuracy at predicting pedestrian behaviour. The better the model performs, the better the interactions are modelled.

3.4. Contribution and implications

Pedestrians interact with all sorts of users, from other vulnerable road users to drivers (of AVs as well as manually driven vehicles). All of these interactions provide information about pedestrian behaviour which can be used to improve prediction models. However, it is hard to evaluate the interactions directly because it is hard to label them to obtain a ground truth. Therefore, we evaluate the interaction predictions by comparing them to the interaction results, i.e. the actual pedestrian behaviour. Our research predicts pedestrian behaviour by considering their interactions with other road users. The original contributions of our research are listed below.

1. We reviewed a large selection of existing papers that used deep learning methods for pedestrian behaviour prediction (Zhang and Berger, 2023). In this study, we provided a comprehensive review of deep learning-based approaches for pedestrian behaviour prediction, and provided a detailed overview of existing datasets and evaluation metrics. We analysed, compared, and discussed the performance of approaches presented in existing works, identified research gaps, and outlined potential future research directions. The interactions of pedestrians played an important role in predicting pedestrian behaviour.
2. We built deep learning models that predict pedestrian trajectories by considering the interactions between pedestrians in crowds (Zhang et al. 2021). We proposed the Social Interaction-Weighted Spatio-Temporal Convolutional Neural Network, a novel approach to capture interactions between pedestrians better and faster.
3. We also considered the interactions between pedestrians and vehicles (Zhang and Berger, 2022a) when predicting pedestrian trajectories. We proposed the Pedestrian-Vehicle Interaction (PVI) extractor to predict pedestrian trajectories, which improved the performance of both LSTM-based and Conv-based prediction networks.
4. We analysed the interactions between pedestrians and AVs (Zhang and Berger, 2022b). We investigated interaction factors using deep learning methods: factors relevant for pedestrian interactions, vehicle interactions, and AV interactions can all influence the accuracy of predictions about pedestrians' future trajectories.

5. To better understand whether a model trained on one dataset can be transferred to other scenarios, we also investigated the transferability of the models (Zhang et al. 2023b). Spectrum features can represent the pedestrian's motion pattern better compared to not using spectrum information and they improve the model's performance. The proposed model demonstrates good prediction accuracy when transferred to target datasets without any prior knowledge.

6. In addition to trajectories, we also investigated the interaction outcomes, especially the crossing decisions of pedestrians at unsignalized crossings (Zhang et al. 2023a). We built machine learning models to predict pedestrians' crossing behaviour when they interact with vehicles at unsignalized crossings. The accuracy of predictions about pedestrian crossing decisions, crossing initiation times, and crossing durations are improved by machine learning models.

3.5. Overview of published results on the topic

Zhang, C., Berger, C., & Dozza, M. (2021). Social-IWSTCNN: A social interaction-weighted spatio- temporal convolutional neural network for pedestrian trajectory prediction in urban traffic scenarios. *2021 IEEE Intelligent Vehicles Symposium (IV).* https://doi.org/10.1109/iv48863.2021.9575958

Zhang, C., & Berger, C. (2022). Learning the pedestrian-vehicle interaction for pedestrian trajectory prediction. *2022 8th International Conference on Control, Automation and Robotics (ICCAR).* https://doi.org/10.1109/iccar55106.2022.9782673

Zhang, C., & Berger, C. (2022). Analysing Factors Influencing Pedestrian Behavior in Urban Traffic Scenarios Using Deep Learning. Accepted in Transport Research Arena (TRA), 2022. Elsevier.

Zhang, C. (2022). Predicting Pedestrian Behavior in Urban Traffic Scenarios Using Deep Learning Methods (Doctoral Licentiate thesis, Chalmers University of Technology).

Zhang, C. (2022). Predicting Pedestrian Behavior in Urban Traffic Scenarios Using Deep Learning Methods (Doctoral Licentiate thesis, Chalmers University of Technology).

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Zhang, C., Ni, Z., & Berger, C. (2023). Spatial-Temporal-Spectral LSTM: A Transferable Model for Pedestrian Trajectory Prediction. IEEE Transactions on Intelligent Vehicles. https://doi.org/10.1109/tiv.2023.3285804

Zhang, C., Kalantari, A. H., Yang, Y., Ni, Z., Markkula, G., Merat, N., & Berger, C. (2023b). Cross or Wait? Predicting Pedestrian Interaction Outcomes at Unsignalized Crossings. *2023 IEEE Intelligent Vehicles Symposium (IV)*. https://doi.org/10.1109/IV55152.2023.10186616

4. Conclusion

To ensure a broad acceptance of AVs in urban environments, these vehicles must not only be safe and provide a significant contribution to the overall traffic safety, we also must design them to be desirable for the users. One of the crucial factors influencing desirability is perceived safety: it is impossible to implement AVs when their behaviour is not perceived as safe by the users. However, perceived safety is subjective, and a better understanding of factors leading to perceived safety is needed. The studies reported in this deliverable provided first steps and interesting results about these factors.

One of the crucial factors that influence whether an AV is perceived as safe is, besides its actual behaviour, whether this behaviour is predictable for the driver inside the vehicle and the road users outside the vehicle. In the studies presented in this deliverable, strategies to increase the predictability of one of the most safety-critical events in the operation of SAE Level 3 AVs – the transition of control from the automation to the driver because of a system limit – was investigated. The results indicate that conveying the level of reliability at which the vehicle is currently operating to the driver is a promising approach to increase the predictability of AV behaviour for drivers, especially for safety-critical situations.

Whereas the above focused on the perception and evaluation of AV behaviour by human drivers or other human road users and on the question how to make these AVs predictable and objectively and subjectively safe, by, for example making their state more transparent, for a safe operation of an AV the AV itself must also be able to understand its environment. An important and crucial aspect of this environment are other road users. Understanding these other road users means for an AV that it possesses behavioural models of them integrated into the algorithms. These models enable the AV to predict the behaviour of other road users and adapt the behaviour according to these predictions. This capability in turn will generate AV behaviour that is in accordance with the human road users' expectations and therefore is predictable for them. This will not only lead to an increased perceived safety of these vehicles but to an increase in actual traffic safety associated with the introduction of AVs into the traffic system.

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