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Deliverable 2.3

Data and data collection methodologies for the development of computational models of AV/VRU interaction and their integration into virtual simulation testing of AV

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Deliverable 2.3 Data collection methodologies for AV/VRU interaction and virtual simulation testing of AV

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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.
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List of Abbreviations

Acronym	Description
AV	Automated vehicle
CAN	Control area network
VRU	Vulnerable road user
ADAS	Advanced driving assistance systems
ADS	Automated driving systems
FOV	Field of view
DTA	Difference in time to arrival
HMD	Head-mounted display
ND	Naturalistic data
WP	Work package
ESR	Early-stage researcher
TUM	Technical University of Munich
TU Delft	Technical University of Delft
Leeds	University of Leeds
UGOT	University of Gothenburg
Chalmers	Chalmers University of Technology
Ulm	University of Ulm
WP	Work package

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Executive Summary

Several computational models explaining interactions between AVs and the VRUs pedestrians and cyclists have been developed in SHAPE-IT. For instance, there are now models predicting whether a pedestrian or cyclist will cross or yield at an intersection. Further, interaction models were developed and/or verified using different types of data collected in experiments or 'in the wild'. These data were combined and fed to different algorithms that leveraged machine learning to describe road-user behaviour.

This deliverable address both pedestrian and cyclist interactions with AVs, utilising both naturalistic data and data collected in controlled environments. The former comprised site-based and in-vehicle data collections. The latter included data from several virtual environments (e.g., driving simulators, riding simulators, and pedestrian simulation environments).

The main conclusion of this deliverable is that the potential for computational models of AV/VRU interaction to promote AV safety while reducing the cost and time of AV development is high. However, more data is needed before human behaviour (especially in critical scenarios) is captured precisely and comprehensively enough that their integration into virtual simulations delivers explainable, accurate, and reliable results. This deliverable is rather a stepping stone to be used to define intermediate goals for the eventual development of computational models of AV/VRU interaction and their integration into virtual simulations for safety benefit assessment.

Within SHAPE-IT, ESR3, ESR13, and ESR14 developed everyday-driving models that may be used directly in traffic simulations, while the focus of ESR15 has been on methods related to and applications of counterfactual simulations.

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Introduction

1.1 AV/VRU interaction: mobility needs and safety threats

The interactions between VRUs and AVs present both mobility opportunities and safety challenges in the evolving landscape of transportation. As self-driving technology advances, the potential benefits of improved traffic flow, reduced congestion, and enhanced accessibility are promising. However, as we transition to a mixed environment where AVs coexist with pedestrians, cyclists, and traditional vehicles, addressing mobility needs and safety threats becomes paramount.

Mobility needs are a key driver in AV/VRU interactions. Autonomous vehicles have the potential to revolutionise transportation for individuals with limited mobility, such as the elderly and people with disabilities. These groups often face barriers in using traditional transportation modes, and AVs could offer newfound independence, enabling them to travel more easily to work, social activities, and healthcare appointments.

Furthermore, AVs can contribute to more efficient urban mobility for all by optimising routes, reducing congestion, and providing seamless integration with public transportation systems. These upgrades will lead to decreased travel times, lower emissions, and enhanced accessibility, particularly in most densely populated areas.

However, ensuring the safety of all road users in this mixed environment is a significant concern. For example, pedestrians and cyclists may have hard-to-predict behaviours that AVs must learn to anticipate. Understanding human behaviour (in order to, for example, detect and respond appropriately to hand signals, sudden movements, and crossings at non-standard locations) poses challenges for AVs' perception systems.

In addition to the challenge of predicting human behaviour, other requirements for AVs to address safety threats include robust sensor systems, reliable communication infrastructure, and comprehensive risk assessment. Cybersecurity is also a critical aspect, as vulnerabilities in AV systems could potentially be exploited by malicious actors, posing risks not only to the AV occupants but also to VRUs and the broader transportation network.

As AV/VRU interactions evolve, public education and awareness campaigns are essential. People need to understand the importance of following traffic rules, respecting the right-of-way, and interacting cautiously with AVs. Meanwhile, developers and regulators must continually refine AV algorithms, validate safety measures, and collaborate with urban planners to design infrastructure that supports safe and efficient AV/VRU coexistence.

In conclusion, the interactions between AVs and VRUs hold great potential to revolutionise mobility, particularly for individuals with limited mobility, while also presenting complex safety challenges. Balancing these opportunities and threats requires ongoing technological advancement, thoughtful regulation, public engagement, and a commitment to creating a transportation ecosystem that prioritises both mobility and safety.

1.2 Computational models for AV/VRU interactions

Computational models play a crucial role in helping researchers understand and improve the interaction between AVs and VRUs. In fact, these models can be used to help researchers, engineers, and policymakers design safer and more efficient transportation systems. Simulations of one or more AVs interacting with one or more VRUs can be used to quantify crash risk, and involving large numbers of AVs and VRUs can simulate safety and travel efficiency at the system level. The models can also be used in real time in AV control systems to predict VRU behaviour and select appropriate AV actions.

Computational models for AV/VRU interactions encompass a range of aspects, including perception, prediction, decision-making, and communication.

- **Perception Models**: AVs need to accurately perceive the presence, location, and intent of VRUs to ensure safe interactions. Perception models use sensor data, such as LiDAR, radar, and cameras, to detect and track VRUs in real time. These models are essential for recognising pedestrians at crosswalks, cyclists in bike lanes, and other dynamic elements in the environment. Improving perception accuracy is critical to prevent accidents and ensure smooth coexistence.

- **Prediction Models**: Predicting the future actions of VRUs is essential for AVs to anticipate and respond appropriately. These models use historical data and real-time observations to forecast the likely trajectories and behaviours of pedestrians and other VRUs. This helps AVs make informed decisions, such as yielding to a pedestrian preparing to cross the street or adjusting speed to accommodate a cyclist's movement. Computational models guide AVs in making safe and efficient decisions when interacting with VRUs. These models integrate perception and prediction data to determine actions like yielding at an intersection, changing lanes, or signalling intentions. The decision-making process considers traffic rules, VRU behaviour, and the AV's objective to minimise risks and promote smooth traffic flow.
- **Decision-making Models:** Understanding human behaviour is a key component in making AV/VRU interactions safe. Computational models that incorporate human psychology, social norms, and cultural factors can enhance the realism of AV behaviour, leading to more predictable and acceptable interactions with VRUs.
- **Communication Models**: AVs and VRUs can benefit from effective communication to enhance safety. Computational models for communication include protocols for AVs to signal their intent to nearby VRUs (e.g., decelerating for pedestrians) and for VRUs to convey their intentions (e.g., hand signals). Ensuring clear and reliable communication is crucial for avoiding misunderstandings and accidents.

As AV technology advances, these computational models must be continuously refined and validated through real-world and virtual-simulation testing to monitor the safety benefits of AV. A multidisciplinary approach involving expertise in computer vision, machine learning, control systems, and transportation engineering is necessary to develop comprehensive models that address the complexity of AV/VRU interactions. The ultimate goal is to create a transportation ecosystem where AVs and VRUs coexist safely and harmoniously, promoting mobility while minimising risks to all road users.

1.3 Virtual simulation testing for safety benefit assessment of AV

To improve traffic safety, many researchers have studied crashes and crash mechanisms to understand why crashes happen. It has been found that human factors contribute to more

than 90% of all traffic crashes (NHTSA, 2015). Therefore, the development of ADAS and ADS, which either assist the driver or drive autonomously (at least under specific conditions), is likely to improve traffic safety, since these systems specifically target the human factors aspects of crash causation.

Safety assessments of ADAS and ADS during their development are necessary to make sure the systems have a positive effect on safety (Jeong & Oh, 2017; Lemmen et al., 2012; Wimmer, 2023), and preferably to quantify the effect size. Further, a system's safety performance needs to be verified before product release to satisfy regulatory constraints (ISO, 2021, 2022) and consumer testing programs (C-NCAP, 2018, 2020; Euro NCAP, 2021, 2022). The safety assessment of ADS is particularly important, as is it taking over the entire driving task; its safety should be compared to human drivers' performance, in order to demonstrate ADS's safety performance both in conflict situations and crash avoidance (UNECE, 2021). The use of virtual simulations to assess safety stands out for its cost effectiveness and flexibility (Yang, 2023). They are especially suitable for fast, iterative system-design assessments during the system development phrase.

There are two main virtual safety assessment approaches: 1) counterfactual simulations and 2) traffic simulations. A main difference between the two is that counterfactual simulations simulate all aspects of the traffic situation under assessment (i.e., everything is modelled), while in traffic simulations virtual representations of individual real-world crashes are used as the baseline, and then compared with the same virtual representations but with the system(s) virtually applied (Bjorvatn et al., 2021). That is, counterfactual simulation relies directly on real-world crashes, simulating what could have happened if the ADAS or ADS had been installed in a vehicle before a specific crash happened (Cicchino, 2017; Sander, 2017, Bjorvatn et al., 2021). Typically, the real-world crash kinematics of (at least) one of the road-users is kept, while other road-users' behaviour may be replaced by computational behaviour models. This approach ensures that the prevalence (exposure) of the individual crashes for which virtual simulations are performed is that of crashes in real traffic. As counterfactual simulations are typically based on a limited set of crash data, scenario generation is sometimes a complementary component in counterfactual simulations (Yang, 2023). However, although counterfactual simulations may also include modifications to the original crashes (i.e., scenario

generation through model parameter variations and the inclusion of models of crash causation; Bärgman et al., 2022), the underlying original-crash exposure is kept in the analysis. On the other hand, in traffic simulation-based safety benefit assessments the exposure must be simulated, which comes with its own challenges.

The second approach, traffic simulation, has been widely used in traffic flow control and environmental assessment (e.g., Bjorvatn et al., 2021). It is also gradually being used to assess safety (Archer, 2005; Bjorvatn et al., 2021). Traffic simulations do not use direct representations of real-world crashes, so computational models of road-user behaviour are needed for all aspects of the simulations (although data from real-world crashes may be used to set the initial conditions of the simulations; Bjorvatn et al., 2021). Both normal everyday driving (non-conflict; Mohammadi et al., 2023, Zhang et al., 2021, Kalantari et al., 2023) and the mechanisms of crash causation must typically be included in the behaviour models (Bärgman et al., 2022, Yang, 2023, Van Lint 2018). Unlike in counterfactual simulations, in traffic simulations the exposure needs to be simulated. In practice, simulating the exposure means that the traffic simulation aims to either a) produce crashes (possibly across conflict scenarios) with the prevalence and severity (e.g., impact speeds) similar to the real world, or b) produce the prevalence (e.g., measured per 1000 km, the number of lane changes or the times to collision under a specific value) of driving scenarios similar to the real world. These numbers are then used as proxies for crash prevalence (Bjorvatn et al., 2021). Simulating exposure with a prevalence value seems to be more common, but this practice has an inherent problem in that the link between the proxies and the crashes they are intended to represent is often far from obvious.

In summary, both counterfactual and traffic simulations require models of road-user behaviours: counterfactual simulations typically include crash-causation models and models of road-user responses to critical events, while traffic simulations also include models of everyday driving. ESR3, ESR13, and ESR14 contributed the development of everyday-driving models that can be used directly in traffic simulation models, while the focus of ESR15 has been on methods related to, and applications of, counterfactual simulations. However, there is some overlap; part of the work of ESR3, ESR13, and ESR14 can also be used in counterfactual simulations, and the methods developed by ESR15 can be used in traffic

simulations. Table 1, below, shows the topic addressed by each ESR and highlights the ESR who contributed to SHAPE-IT with road-user behaviour modelling.

Table 1- Topics of the early-stage researchers (ESR) in SHAPE-IT (italics indicate a direct contribution to this deliverable).

ESR	Title and related work package (WP) within SHAPE-IT	Institution
1	Understanding Driver/AV Interaction Using Neuroergonomics (WP1)	Ulm
2	Long-Term Effects of Automation on User Behaviour (WP1)	TUM
3	Predicting Pedestrian Behaviour Considering Interactions Between AVs/vehicles and Pedestrians Using AI (WP2)	UGOT
4	Long Term Effects of AV Exposure on AV/VRU Interactions (WP1)	Leeds
5	Developing more comfortable, pleasant, and acceptable AV-kinematic cues for drivers (WP1)	Leeds
6	Internal Interface for Transparent Automation (WP1)	Ulm
7	Assessing AV Transparency (WP1)	TUM
8	Human Factors in AI-based Automation Design (WP1)	UGOT
9	Assessing Interactions Between AVs and VRUs Using Virtual/Augmented Reality (WP2)	TU Delft
10	HMIs Promoting Safe AV/cyclist Interactions (WP2)	TU Delft
11	Cooperative Interaction Strategies Between AVs and Mixed Motorised Traffic (WP2)	Ulm
12	AV Occupants Perception of Safety in Relation to AV Behaviour (WP1)	TU Delft
13	Computational Vehicle/Pedestrian Interaction Models (WP2)	Leeds
14	Computational AV/Cyclist Interaction Models (WP2)	Chalmers
15	Safety Evaluation of Automation Using Counterfactual Simulations	Chalmers

2 Data for computational models of AV/VRU interaction

Data for transportation research may be collected from different environments. Some enable more control over the experimental conditions than others. Usually, as the environment is more controlled, the collected data becomes “cleaner” but less ecologically valid. For instance, driving simulators may provide very consistent experimental conditions across participants; however, the environment is artificial. The extent to which the data are representative of real-world conditions must be evaluated from case to case. On the other end of the spectrum,

naturalistic studies produce data with high ecological validity, but the environmental conditions are entirely uncontrolled and can vary widely across participants. Below, we introduce the different methodologies for data collection employed in SHAPE-IT and present the actual datasets that SHAPE-IT analysed.

2.1 Controlled environments

2.1.1 Driving simulators

Driving simulators are advanced tools used to replicate real-world driving environments and scenarios. They are often equipped with a realistic cockpit that mimics the interior of a typical vehicle, providing an immersive experience for the driver (Figure 1). Driving simulators are routinely used by the automotive industry and research community, resulting in extensive human-behaviour data representing active drivers and AV users.

The visual environment in a driving simulator is usually projected onto a wide, curved screen (often covering 180 degrees or more), using high-quality projectors. The goal is to create a realistic driving experience that closely resembles the road and surroundings that a driver would actually encounter.

Various software solutions are employed to design and control the traffic environment within the simulator. These tools allow the customisation of road conditions, traffic patterns, and vehicle dynamics, enabling researchers to simulate a wide range of driving scenarios.

The vehicle's dynamics, including acceleration, braking, and steering, are controlled in real time using specialised simulation systems. Data related to the vehicle's movement and the surrounding traffic can be logged and analysed, providing valuable insights into driver behaviour and vehicle performance.

Many driving simulators also include features that simulate automated driving functions such as Adaptive Cruise Control (ACC). These algorithms can be implemented and tested within the simulator, allowing researchers to explore the interactions between automated vehicles and human drivers.

The Human-Machine Interface (HMI) within the simulator often includes indicators and warnings that inform the driver about the status of various systems. These indicators and

warnings can include visual cues, such as colour-coded warnings to signal that the driver needs to take control or indicators to show that an automated system is functioning properly.

Overall, driving simulators provide a controlled, safe environment for studying and understanding complex interactions between vehicles, drivers, and the road. They are valuable tools in the development and testing of both conventional and autonomous driving technologies, contributing to advancements in safety, efficiency, and the overall driving experience.

Figure 1- Delft Advanced Vehicle Simulator (DAVSi) at Delft University of Technology

2.1.2 Riding simulators

Riding simulators, advanced virtual environments designed to replicate real-world cycling experiences, offer a range of benefits for testing scenarios involving cyclists. These simulators leverage cutting-edge technology to provide a highly immersive and controlled training environment, allowing researchers to investigate different aspects of cyclists' behaviour, especially when they interact with AVs. It is only very recently that a range of riding simulators has been introduced; few studies have validated them and used them to study rider behaviour. Here are some key benefits of cycling simulators:

- **Realistic Interaction Scenarios**: Cycling simulators can replicate a wide range of real-world interaction scenarios between cyclists and AVs. Realism is crucial for capturing the complexities of road interactions, including merging, passing, yielding, and reacting to unexpected events. By studying various scenarios, researchers can better understand the dynamics of AV-cyclist interactions and fine-tune their models accordingly.

- **Controlled Environment**: Simulators provide a controlled environment, which is essential for isolating specific factors and variables that influence AV-cyclist interactions. Researchers can manipulate parameters such as AV behaviour, cyclist actions, road conditions, and traffic density to study how these elements impact the safety and efficiency of the interaction.
- **Data Generation**: Cycling simulators can generate extensive datasets capturing AV-cyclist interactions. These datasets serve as valuable inputs for training and validating computational models. Researchers can use the data to analyse the effectiveness of AV detection, prediction, and decision-making algorithms when encountering cyclists.
- **Iterative Model Improvement**: Simulators allow researchers to iterate and refine their computational models rapidly. By comparing simulated results with real-world observations or benchmark data, researchers can identify areas where the models need improvement. This iterative process accelerates the development of more accurate and reliable models of AV-cyclist interactions.
- **Safety**: Safety is a paramount concern when studying AV-cyclist interactions. Cycling simulators provide a risk-free environment to test and validate AV algorithms and cyclist-awareness features before the AVs are brought to market. This process ensures that AVs can reliably detect and respond to cyclists' actions, reducing the likelihood of accidents when these technologies are deployed on the road.
- **Customisation and Scalability**: Cycling simulators can be customised to represent specific cities, road layouts, and cycling infrastructure, which enables researchers to study AV-cyclist interactions in diverse urban environments. Additionally, simulators can scale up to simulate high-density cyclist scenarios, which is challenging to achieve in real-world testing.
- **Efficiency**: Conducting experiments in cycling simulators is more efficient than conducting large-scale on-road tests. Researchers can simulate numerous interactions in a shorter time frame and with relatively lower cost compared to other data collection methods, allowing them to gather a wealth of data to validate their models comprehensively.

It is worth noticing that the bullets above also apply to driving simulators. However, cycling simulators may also try to recreate the balancing task that cyclists perform while riding (but is not necessary for drivers). Further, cycling simulators often use head-mounted displays (HMDs) to provide full immersion for the cyclist. This addition makes the environment more realistic by, for instance, making it possible to perform shoulder-checks; however, it also contributes to motion sickness. In other words, the fully immersive, dynamic experience makes experiments in the cycling simulator more vulnerable to drop-outs because of nausea than driving simulators.

In summary, cycling simulators offer a controlled, efficient platform for observing cyclists' behaviour. However, the extent to which the environment in the simulator is ecologically valid should be evaluated in a different study. Even though data collection in simulators is more straightforward than naturalistic data collection, a significant amount of time should be dedicated to preparing a realistic scenario in the simulators. In the picture below the cycling simulator that was used in ESR 14's study is depicted.

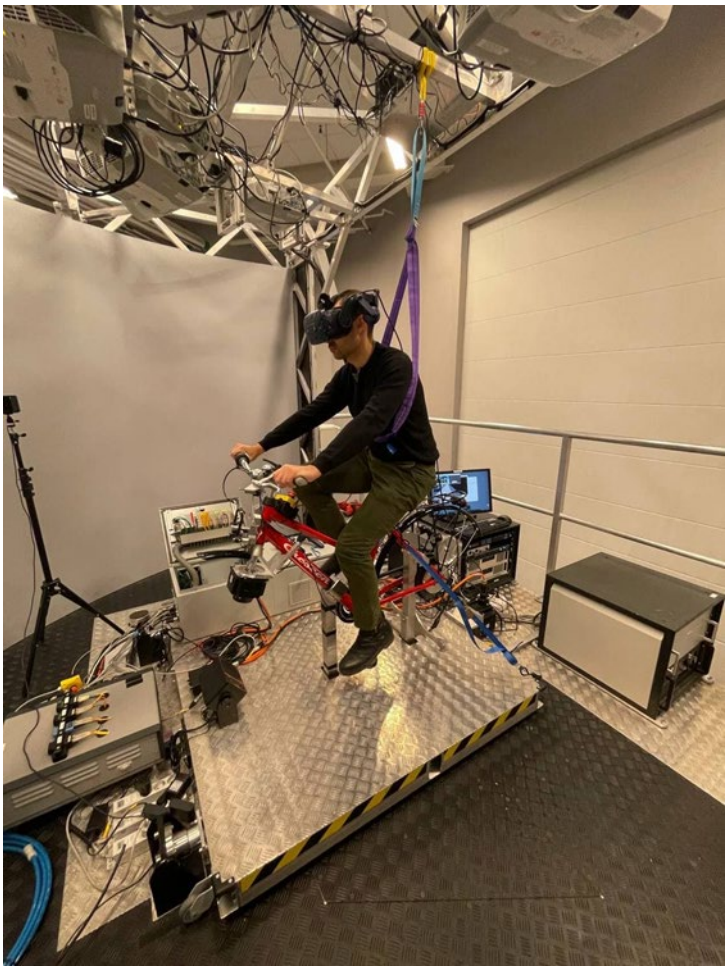

Figure 2- Cycling simulator at VTI facilities

2.1.3 Pedestrian simulation environments

Pedestrian simulation environments for experiments are usually created using HMDs and CAVE (Cave Automatic Virtual Environment) systems. Irrespective of which display type is used, pedestrian simulators vary based on their potential to provide stereo vision (depth perception) and the inclusion of auditory cues. Pedestrian simulators enable virtual movement through manual control (using devices like joysticks or keyboards), natural walking, and treadmill usage. It has been shown that factors such as display type, presence and type of auditory feedback, and the ability to replicate walking movements can influence how pedestrians behave in simulated environments (Schneider & Bengler, 2020).

The use of HMDs is cost-effective and convenient, requiring only a helmet featuring 3D goggles that project high-quality images and a space for walking (Mestre, 2017). Additionally, HMDs are intrinsically different than stationary displays. Despite their limited field of vision (around 110° vertically and 100° horizontally), HMDs offer a 360° panoramic perspective, enhancing the sense of immersion by isolating the viewer from the real world (LaViola Jr et al., 2017).

The CAVE system is composed of expansive screens that project computer-generated images of high resolution, delivering an immersive experience for users. This arrangement facilitates the naturalistic observation and measurement of realistic street-crossing scenarios (Pala et al., 2021b). Figure 3 shows the Highly Immersive Kinematic Experimental Research (HIKER) CAVE-based lab at the University of Leeds, where ESR 13 conducted his research on pedestrians.

Figure 3- The HIKER pedestrian lab at the University of Leeds

A comparison of HMDs and CAVE reveals that each has advantages and disadvantages. Previous research suggests that HMDs can induce motion sickness (Deb et al., 2017) and postural instability (Robert et al., 2016), whereas CAVE technology may limit these issues but it is more costly and requires more space than HMDs. Additionally, unlike HMDs, the immersive sensation of the CAVE can be disrupted—if users look at areas lacking screens (Pala et al., 2021a).

2.2 Naturalistic approaches

Real-world behaviour data, or so-called naturalistic data, can be collected through site-based observation or vehicle-based observation.

2.2.1 Site-based

Site-based traffic data collection is a fundamental component of naturalistic data collection when the focus is on studying transportation and mobility patterns. In this approach, various data collection tools (such as traffic cameras, sensors, and GPS tracking devices) are deployed at specific locations within the transportation network (such as intersections or highways). These tools enable researchers to passively monitor and record real-world traffic, including vehicle speeds, traffic flow, congestion patterns, and driver behaviours. By gathering data directly from the traffic sites, researchers can unobtrusively gain an authentic perspective on how people navigate within the transportation system and interact with each other. This wealth of site-specific traffic data plays a vital role in improving traffic management, road safety, and urban planning, ultimately contributing to more efficient and sustainable transportation systems.

Figure 4- View from mounted sensor capable of extracting road users' trajectories at an unsignalised intersection

Site-based data collection has numerous benefits, like accurate real-world data which reflects actual traffic conditions and behaviours. In addition, this type of data collection is cost effective, and the data are valuable resources for validating and cross-checking data obtained from other sources. In summary, site-based traffic data collection is a valuable methodology for transportation professionals, researchers, and policymakers, offering a wealth of detailed, real-world information that can enhance traffic management, safety, and overall urban planning.

2.2.2 Vehicle-based

Naturalistic driving data collection methods focus on observing drivers in real-world, everyday driving scenarios without intervention, generally over extended periods. This approach captures a comprehensive picture of driver behaviour, road user interactions, and potential risk factors under actual conditions. As technology has advanced, various methods for collecting naturalistic data have emerged. Initial approaches often involved mounting cameras

on tall buildings to observe interactions between various road users, such as vehicles and VRUs. Over the past two decades, the vehicle-based data collection method has become increasingly popular. This method involves fitting vehicles with advanced instrumentation, including cameras, radars, and control area network (CAN) systems, to capture detailed driving behaviour and interactions in real-world conditions. Multiple cameras are mounted to record both the driver's actions inside the vehicle and the traffic conditions outside, as shown in Figure 5. Radars are typically used to monitor the distance and relative speed between the equipped vehicle and other road users. The CAN data gathers real-time information about vehicle speed, throttle position, brake application, steering angle, and many other parameters. Together, this multifaceted data collection approach is crucial for deriving meaningful insights and making informed decisions about road safety, driver education, and vehicle design. Some of the largest vehicle-based naturalistic data collection initiatives include SHRP2 (Second Strategic Highway Research Program) in the United States (Antin et al., 2019) and UDRIVE (Eenink et al., 2014) and L3Pilot (Rösener et al., 2019) in Europe.

Figure 5- Instrumented vehicle to collect naturalistic driving data (published with author's permission)

The vehicle-based data collection method offers several benefits. Firstly, it provides an unobtrusive way to observe drivers in their natural settings without the potential bias introduced by laboratory simulations or observer presence. Such genuine data is invaluable in understanding real-world driving habits, distractions, and decision-making processes in variety of traffic conditions, such as a driver's response to a pedestrian (Rasch et al., 2020) or while overtaking a cyclist (Kovaceva et al., 2019). Additionally, with the aid of technologies like radars and CAN, intricate details about vehicle operation, such as acceleration patterns, braking intensity, and steering angles, can be recorded, offering a holistic view of driving scenarios.

2.3 Data and data collection in SHAPE-IT

2.3.1 Data collected in SHAPE-IT

Data from the riding simulator at VTI, Gothenburg, Sweden

A bike simulator was used to collect data from participants riding through an unsignalised intersection. Participants were instructed to pass the intersection several times. The environment was shown to the participants by a virtual reality headset. As the participants neared the intersection, a car approached from the right, and they needed to decide what to do. The effects of the difference in time to arrival at the intersection (DTA) and the field of view (FOV) distance on the cyclists' response process were investigated. Sensory and questionnaire data were used to determine how cyclists interact with cars and what the influencing factors in their decision-making are. Participants filled out a questionnaire about their experience in the simulator after the test.

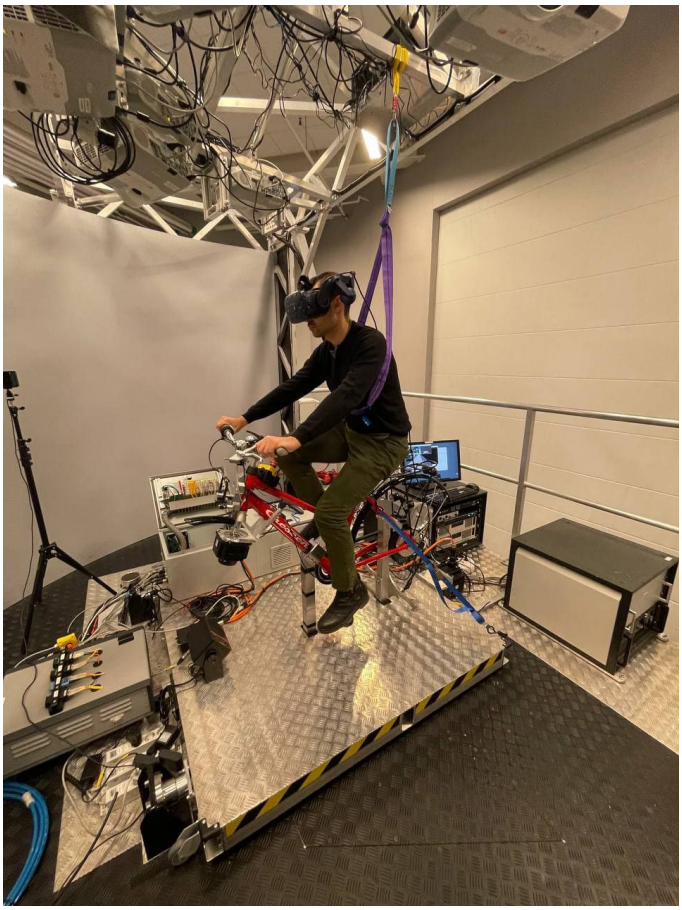

Figure 6- Riding simulator

Data from the pedestrian simulator at the University of Leeds, UK

Pedestrian data were collected in a CAVE-based pedestrian lab (the HIKER lab) as part of a distributed simulator study (Figure 7). In this study, 32 driver-pedestrian pairs interacted with each other under different scenarios consisting of different vehicle kinematics and crossing location types. The pedestrians wore 14 motion trackers (attached to their head, arms, chest, pelvis, elbows, hands, thighs, ankles, and feet) to track their position as they moved freely during the experiment. They were represented as a group of pink spheres to the drivers. Ten VICON Vero v2.2 cameras were placed on the upper edges of the glass walls of HIKER, with their signals processed by a VICON Tracker (version 3.7). The virtual reality presented to the

participant responded to their head movements through the use of HIKER glasses, ensuring a perspective-correct experience. The pedestrians were instructed to stand at a designated point on the HIKER floor, where they could see cars going both ways on a two-way road but could not anticipate when the human-driven vehicle would approach. They were told to step forward to the next designated point once they heard an auditory prompt. The second point was placed at the curb of the virtual road, where they needed to decide whether to cross in front of the vehicle or wait for it to pass first. Road user interaction outcome (i.e., pedestrians crossed first or waited), trajectories, and kinematics (including pedestrians' crossing initiation/duration time, walking speed, and waiting time) were recorded throughout the experiment (Kalantari, Yang, Pedro, et al., 2023).

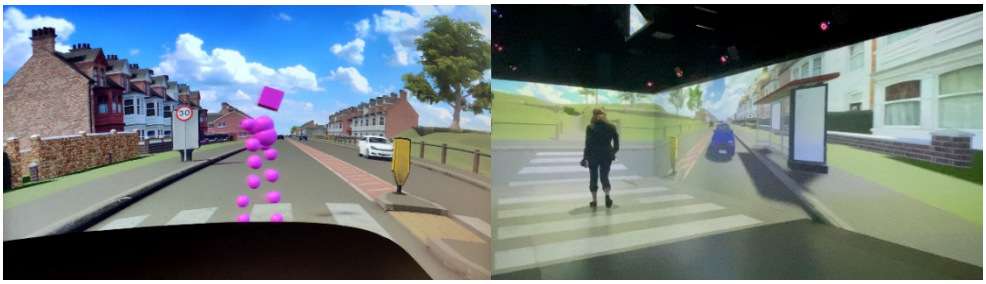

Figure 7- The driver's view of the pedestrian (left) and the pedestrian's view of the vehicle in the HIKER lab (right)

Data from the driving simulator at TME, Brussels, Belgium

A driving simulator was used to observe drivers' behaviour when they interact with an approaching cyclist at an unsignalised intersection. Participants were instructed to cross the same intersection several times and interact with an approaching cyclist at the intersection. The independent variables in this study consisted of the cyclist's speed, DTA, and visibility condition (i.e., how early the cyclist was visible for the driver). Sensory data from this experiment included vehicle position and speed as well as gas- and brake-pedal use. In addition, questionnaire data about participant's' experience inside the simulator and demographics were collected after the experiments.

Data from the driving simulator at the University of Delft, Netherlands

The motorway driving environments used for collecting data on perceived risk and trust were meticulously created on the Delft Advanced Vehicle Simulator (DAVSi), equipped with a Yaris cockpit (Fig. x).

Figure 8- Delft Advanced Vehicle Simulator (DAVSi) at Delft University of Technology

The immersive environment is projected onto a cylindrical 180-degree screen by three high-quality projectors, providing a realistic driving experience (Khusro et al., 2020). CarMaker 8.0.1 software was utilised to craft the motorway traffic environment, while an Auris 4 model was employed to simulate the subject vehicle's dynamics. The dynamics and surrounding traffic were controlled in real time using Simulink on the dSPACE SCALEXIO simulation system. Motion data for the subject vehicle and other vehicles were logged at a frequency of 10 Hz. Automated lateral control of the subject vehicle was executed by the IPG driver model provided by CarMaker. A non-linear full-range Adaptive Cruise Control (ACC) algorithm was implemented (Mullakkal-Babu et al., 2016). The Human-Machine Interface (HMI) was a simple indicator on the dashboard, displaying the automation's working status through two colours: green (indicating that the system is activated and functioning properly) and yellow (warning the driver to take over control). This setup provided a controlled environment for understanding and modelling some of the complex interactions between AVs and VRUs, contributing valuable insights to the field of autonomous driving technology.

Continuous perceived risk data were collected by a pressure sensor fixed on the steering wheel (Fig. xA), obtaining visual feedback through an LED bar (Fig. xB). The participants were tasked to press the sensor whenever they felt unsafe; the harder they pressed, the more unsafe they felt. So, no force (zero active LEDs) indicates no perceived risk and the maximum

(ten active LEDs) means very high risk. The continuous rating was recorded at 60 Hz. Three physiological signals were measured to assess their predictive value for trust and perceived risk: cardiovascular activity (ECG), galvanic skin response (GSR), and pupil dilation. ECG was measured on Lead II (between the left inner ankle and right inner wrist, with the ground on the right inner ankle) and recorded using a TMSi amplifier at 1024 Hz (Fig. xC). Heartbeats were identified using BioSigKit (Sedghamiz, 2018). GSR was measured on the right palm with a Groove GSR sensor at 60 Hz and de-convolved into phasic and tonic components using Ledalab-349 (Benedek and Kaernbach, 2010). Pupil dilation (diameter) of the left eye was measured at 50 Hz using a Tobii head-mounted eye tracker (Fig. xD) and postprocessed with a 4 Hz low-pass filter (Kret and Sjak-Shie, 2019).

(a) (b) (c) (d)

Figure 9- (a) Pressure sensor for reporting continuous perceived risk. (b) LED bar- Visual feedback of reported continuous perceived risk. (c) ECG device TMSi to measure cardiovascular activity (d) Eye tracker Tobii Pro Glasses 2 to measure pupil dilation.

Several experiments were conducted, resulting in models of perceived risk and trust for AV users (He et al., 2022). The findings demonstrate that interfaces showing (or verbally communicating) what the AV perceives and what actions it takes convey many benefits, such as enhancing users' perceived safety and trust in, and acceptance, of AVs (Nordhoff et al., 2021).

Naturalistic data from Viscando systems in the UK

A naturalistic study conducted in Leeds, UK used state-of-the-art sensors to investigate road user interactions in real time. Two Viscando camera sensors, known as OTUS3D, were utilised for the data collection. The sensors collected road user type and trajectory over discrete time intervals. Two marked crossings were selected based on safety concerns (a

history of many crashes) and the prevalence of one-to-one vehicle-pedestrian interactions. One is a staggered crossing situated at Belle Isle Road (53°46′07″N, 001°31′48″W) and the other is a zebra crossing on Queensway Road (53°44′45″N, 001°36′16″W). Data was gathered over a period of 14 days, with each location being observed for seven days. Road user interaction outcome, time, position, and movement-based factors were analysed and modelled. The findings of the study were compared to those of the simulator study.

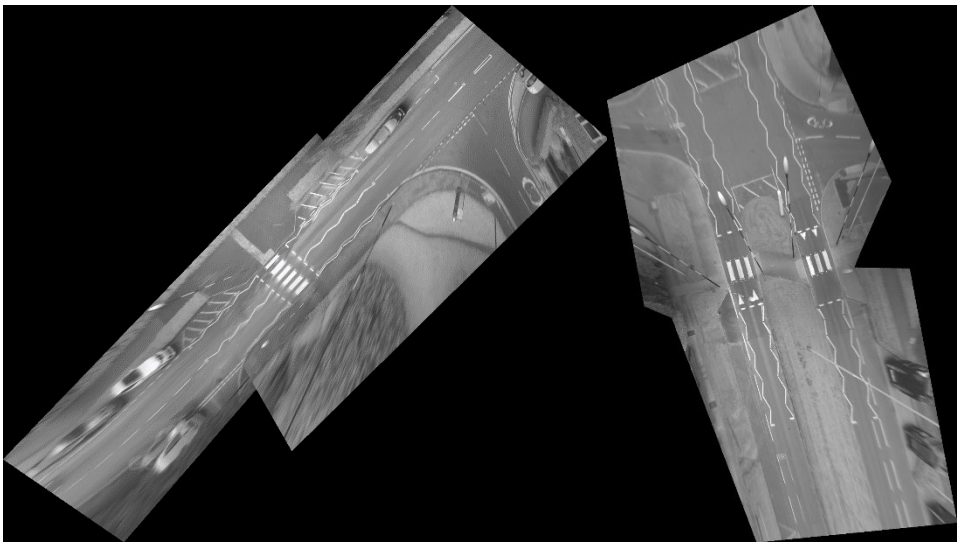

Figure 10- Bird's eye view of Queensway Road (left) and Belle Isle Road (right)

2.3.2 Data from the SHAPE-IT partners

Naturalistic data from Viscando systems in Sweden

Data were also from an unsignalised intersection in Gothenburg, Sweden, using Stereovision and an AI-based sensor from Viscando. Fourteen days of data were collected from the intersection and trajectories of all the road users were recorded. Data were gathered each day between 6:00 and 18:00. The identified groups of road users included pedestrians, cyclists, vehicles, and heavy vehicles. The trajectory information encompassed positions, speeds, and headings, all recorded at a rate of 20 Hz. These data were made available to

SHAPE-IT and used to model the interaction between cyclists and drivers. The models provide a reference driver whose behaviour can be compared to that of AVs as well as predictive algorithms which AVs can use to make interactions with cyclists safer.

2.3.3 Open datasets in SHAPE-IT

High-quality datasets are important for modelling VRU behaviour. For pedestrian behaviour prediction, we reviewed a large selection of existing studies to identify useful tools for prediction and open datasets that are commonly used for evaluation (Zhang and Berger, 2023). The same effort was made for cyclist behaviour prediction; however, within SHAPE-IT we only used open data for modelling pedestrians' behaviour. Using open data for modelling cyclist interactions was not as appealing, for many reasons. One reason was that their quality was not as high as the alternative datasets we had available or could acquire within our facilities, especially considering the specific scenario (unsignalised intersections) that we targeted. Further, open datasets often provide only trajectory data and we also wanted to consider non-kinematic-related factors (e.g., gestures or helmet wearing) in our modelling effort. The two open datasets that SHAPE-IT used for modelling pedestrian behaviour both included naturalistic data.

Waymo Open Dataset (naturalistic)

The Waymo Open Dataset (Sun et al., 2020) is a large-scale, real-world open dataset collected in road scenarios. It contains 1,150 scenarios (recently updated in March 2023 to 2,030 segments) that each last 20 seconds, collected from the vehicle's view. The data were collected with high-resolution cameras and LIDARs. The urban street scenarios were used in our research to investigate pedestrian behaviour (Zhang et al., 2021, Zhang and Berger, 2022a, Zhang and Berger, 2022b, Zhang, 2022, Zhang et al. 2023b).

The 450 urban scenarios include 374 training records and 76 test records. The ground truth of pedestrian behaviour is annotated with 2D and 3D positions on camera and LIDAR images. In our research we used the 3D position data for trajectory prediction. Public URL: https://waymo.com/open/.

Figure 11- A snapshot of an urban traffic scenario in the Waymo Open Dataset (Sun et al., 2020)

ETH and UCY Datasets (naturalistic)

The ETH (Pellegrini et al., 2009) and UCY (Lerner et al., 2007) datasets are popular and widely used for studies on pedestrian trajectory prediction. These two datasets contain five fixed scenarios, collected from a bird's-eye view using a camera. These datasets were used in our research to investigate the transferability of our models (Zhang et al., 2023b).

Public URL:

- ETH (accessed on 2023 Aug 14):
  https://icu.ee.ethz.ch/research/datsets.html
  download:
  https://ethz.ch/content/dam/ethz/special-interest/itet/cvl/vision-dam/documents/ewap_dataset_light.tgz
  https://data.vision.ee.ethz.ch/cvl/aem/ewap_dataset_full.tgz

- UCY (accessed on 2023 Aug 14):
  https://graphics.cs.ucy.ac.cy/home
  download:
  https://graphics.cs.ucy.ac.cy/research/downloads/crowd-data

Figure 12- A snapshot of a scenario in the ETH (Pellegrini et al., 2009) dataset.

Figure 13- A snapshot of a scenario in the UCY (Lerner et al., 2007) dataset.

2.4 Data and data collection challenges from SHAPE-IT experience

2.4.1 Methodology limitations

Each data type comes with limitations which are often due to a trade-off between costs, experimental control, safety, and ethical considerations during the collection phase. Therefore, not all methodology limitations can be overcome. It is fundamental for the analyst to be aware of the limitations in order to make the best use of the data. In other words, understanding the constraints of the acquisition methodology makes it possible to appreciate the validity of the results from the data analysis. It is also important to understand how to combine datatypes to leverage their advantages and compensate for their disadvantages. As an example, simulator data may be easier to use for developing behavioural models, while real-world data may be best for the models' validation.

Riding, driving, and walking simulator (controlled environments)

Riding Simulator

The experiment faced a limitation in terms of participant recruitment, partly because of the on-going pandemic. Further, motion sickness led a significant number of participants to drop out, affecting data collection. Unfortunately, the ecological validity of the riding simulator is unknown, because (as is the case for most simulators) it has not been validated with real-world data.

Driving Simulator

The TU Delft study included highway driving, a situation in which car simulators are widely applied; they are considered valid but not perfect. No motion sickness was reported.

In the study involving urban interactions with cyclists, motion sickness resulted in a high dropout rate among participants in the driving simulator. As with the riding simulator, the ecological validity of the results from the driving simulator is hard to estimate, especially because creating a realistic interaction scenario with cyclists within the driving simulation environment posed challenges.

Simulated environments lacking real-world motion could create disparities in perception and response, potentially affecting the simulation's validity. Variations in brightness within the simulation were found to significantly impact pupil dilation, potentially complicating the analysis of that physiological response's relation to perceived risk. Further, controlled scenarios in the driving simulations tended to become predictable after repeated trials, introducing learning effects that may have introduced bias in the results.

Walking Simulator

In the walking simulator study, pedestrians and drivers were unable to perceive each other before pedestrians reached the curb, leading to limits in the interaction approach phase. The influence of pedestrian group size on interaction outcomes was disregarded due to limitations in the simulator's capacity (the simulator is meant for one person). The use of spheres for pedestrians instead of more realistic, calibrated avatars hindered the study of pedestrian pose, gait, and eye contact in interactive behaviours.

Overall, these limitations underscore the need for careful consideration and interpretation of data collected from simulators, particularly when assessing their applicability to real-world scenarios and interactions.

Naturalistic studies (uncontrolled environment)

Critical Events

The utilisation of naturalistic data for modelling interactions is subject to several limitations. Firstly, the dataset may feature only a small number of critical interaction events, potentially failing to represent the diversity and comprehensiveness of the interactions under study. The limited variety will inevitably constrain the model's ability to encompass the full spectrum of real-world scenarios. Additionally, distances estimated from cameras may not be sufficiently precise or accurate, which could affect the fidelity of the results of the modelling process and, in turn, the model's performance in predicting road-user behaviour. Furthermore, when the data collection process occurs exclusively at a single location, data are inevitably biased. This geographical constraint can limit the applicability and generalisability of the resultant models, as they may not effectively account for the variability of interactions across different settings.

Road User Behaviour

When applying naturalistic data to model road user interactions, the researcher needs to understand certain limitations related to the scope of the study that produced the data. Specifically, due to the specific modelling objectives, the analysis focused solely on one-on-one car-road-user interactions, without considering multiagent interactions which might be of interest in future research endeavours. Furthermore, interactions involving different vehicle types and pedestrians were omitted from the study, due to the complexity of the modelling requirements. It is important to recognise that the exploration of road user behaviour was confined to a single driving lane and direction: the specific infrastructure under consideration also imposed limitations. This point may be particularly important for pedestrian behaviour analysis, as previous research findings suggest that pedestrians might exhibit different behaviour patterns on streets with two-way traffic (Dommès et al., 2021).

Large Data

Employing naturalistic data sets for modelling interactions within dynamic environments presents a series of computational and practical challenges. Notably, the continuous operation of an array of sensors generates voluminous datasets that necessitate substantial computational resources for storage, processing, and subsequent analysis. Moreover, the installation and upkeep of the data acquisition system entail considerable financial expense. Ensuring consistent data quality across various vehicles/collection sites also poses a formidable challenge. Addressing these challenges demands robust methodologies and strategies for data management and maintenance. In addition to these technical considerations, privacy emerges as a pivotal concern. The collection of video footage and data from real-world driving situations carries the inadvertent risk of capturing personal and sensitive information, with the potential to create ethical and legal dilemmas. Finally, humans are still in part responsible for video reduction, adding a subjective dimension to the interpretation of naturalistic data.

Complexity in pedestrian behaviour

The utilisation of naturalistic data for modelling pedestrian interactions introduces inherent complexities and limitations that warrant careful consideration. One central challenge involves disentangling a pedestrian's initial intention from their actual observed actions within the naturalistic data. This difficulty in discerning intention-action dynamics can impede accurate interpretation and analysis. Furthermore, extracting information about pedestrians' personality traits from the data has proven to be impractical so far. The intricate interplay of latent variables that can influence pedestrian behaviour further complicates the study of interaction factors. Developing effective algorithms based on naturalistic data necessitates meticulously labelled datasets, a resource-intensive endeavour. The cost associated with producing well-annotated data might serve as a barrier to algorithm development and refinement (Zhang, 2022; Zhang et al., 2023a).

2.4.2 Data limitations

The issue of incomplete data, which can stem from sensor failures, is a recurring one. Alongside this, noisy data can introduce errors and inaccuracies into the dataset, as noted by

Singh and Kathuria (2021). Additionally (and as mentioned before), the vast amount of data available, coupled with limited computational resources, makes the processing of data a challenging task.

The available sample size of the data can significantly impact the reliability of research outcomes. Inadequate sample sizes may fail to capture the full range of driving behaviours, rendering analyses less comprehensive. Moreover, data collected from surveys, naturalistic driving studies, or driving simulators may carry inconsistencies, inaccuracies, or biases that affect the robustness of predictive models. Such biases can arise from factors like the location of data collection, demographics of the studied population, or the sampling methods.

Even well-established open datasets, such as ETH and UCY, have intrinsic limitations, as pointed out by Zhang et al. (2021). These datasets might not possess the necessary size and diversity to comprehensively represent the subject matter. For instance, the exclusion of densely populated urban traffic situations and pedestrian-vehicle interactions in these datasets can impact the applicability of findings based on them. Similarly, the Waymo Open Dataset's focus on the US might omit considerations vital for low-income countries. Factors like geographical variations, crowd densities, and cultural influences might not be captured if they do not align with the dataset's scope.

Certain datasets suffer from limitations in data collection frequency, particularly in capturing fine-grained details of driving behaviour. This is particularly true for event data recorder data, as highlighted by NHTSA (Thomson et al., 2013). Moreover, data obtained from real crash scenarios tend to favour more severe crashes, resulting in the under-representation of non-injury or low-severity crashes. This bias impacts the overall understanding of crash dynamics.

Limited data availability from a single location can hinder the generalisation of research findings to broader populations. In studies involving simulators, the issue of motion sickness can introduce bias into the data collection. Furthermore, discrepancies in accuracy between naturalistic driving datasets and simulator-generated data can complicate comparisons. Efforts to enhance datasets, such as adding specific features, can require substantial preparation efforts.

The role and quantity of confounding variables in naturalistic data often remain undetermined, leading to correlational rather than causal relationships between variables. Simulators, while valuable, might lack scenarios that involve varying constant speeds of approaching vehicles. Additionally, both lab and naturalistic data tend to lack critical scenarios like crashes and near-crashes, essential for some specific applications, like testing autonomous vehicles. These limitations constrain the scope of investigations and modelling possibilities.

Data related to perceived risk have their own set of limitations. Perceived risk data collected without vehicle motion may introduce bias, as it fails to replicate the complete driving experience. Physiological signals used to assess perceived risk might not provide the precision required for computational modelling, especially in less obviously hazardous situations. The focus on specific driving scenarios in simulator-based studies, while valuable, overlooks aspects like lateral risk and lacks broader generalisability. Human-Machine Interface effects are often omitted, reducing the comprehensiveness of analyses focused on driver behaviour and perception.

For any researcher, navigating data limitations is integral to gauging the accuracy and reliability of research outcomes. Acknowledging these challenges is the first step in devising strategies to minimise their impact, enhance the validity of findings, and interpret the results for what they are. While data constraints may pose hurdles, addressing them paves the way for more informed, nuanced insights in research.

2.5 How to improve data and data collection, according to SHAPE-IT

- **Enriching Data Quantity and Quality**

To fuel robust analyses, it is imperative to expand the sample size. Embrace a wider spectrum of participants by avoiding geographical and demographic limitations. Collaborative efforts and sensor synchronisation harmonise data inputs, bolstering quality. Employing random sampling strategies mitigates bias, ensuring a representative dataset.

- **Innovating Data Representation in Pedestrian Studies**

In pedestrian studies, calibrated avatars would transcend simplistic representations, enhancing realism. Incorporate scenarios featuring complex interactions, like two-lane road

crossings. Leverage networked HMIs to analyse group dynamics. Make use of diverse scenarios encompassing intersections and jaywalking behaviours, to encompass the breadth of real-world interactions.

- **Integrating Multi-Agent Scenarios and Mixed-Method Approaches**

Extend data collection to scenarios involving multi-agent dynamics. Capture the intricacies of real-world interactions by embracing a mixed-method approach, which entails merging passive crash reports with active site-based data collection, in order to foster a holistic understanding of location-specific incidents.

- **Enhancing Realism in Simulated Environments**

Simulated environments offer controlled settings, yet incorporating motion cues bridges the gap between these and real-world experiences. Consistent lighting conditions, crucial for eye-tracking data, ensure accurate metrics. Implementing randomisation in scenario selection minimises learning effects, rendering collected data more authentic and valid.

- **Bridging Simulation and Reality for Holistic Insights**

For a well-rounded dataset, consider on-road testing alongside simulations. Real-world conditions provide nuanced insights often overlooked in controlled settings. Urban environments and varied scenarios enrich perceived-risk data, amplifying the dataset's applicability. Delve into Human-Machine Interface (HMI) impact in order to decode driver responses to automated systems comprehensively.

In conclusion, the journey to enhance data and data collection transcends individual research domains and projects. By unifying strategies that amplify quantity, quality, and realism, while embracing diverse scenarios and innovative approaches, we pave the way for more profound insights in future research projects. Advances in technology may help overcome many limitations in data collection, by providing more cost-effective solutions and better sensing.

3 Challenges for the integration of computational models into virtual simulations

Computational road-user models are widely used in virtual simulations for safety benefit assessment. The models play a pivotal role in simulating traffic interactions, finding application in various contexts such as traffic simulations and counterfactual simulations. There are several challenges with integrating computational models into virtual simulations for system performance assessment. These include the differences in data needs and data availability across models and across safety benefit assessment approaches, software interoperability, and computational load and simulation optimisation. These topics are described in turn.

3.1 Data availability and data needs across models and across assessment approaches

The main reason it is difficult to use virtual safety benefit assessments to assess different safety solutions is the lack of data available to develop crash causation and critical event response models. Both traffic simulations and counterfactual simulations require such models. Traffic simulations also require everyday traffic-interaction models, but those data can be collected in relatively short times (and at relatively low cost), either naturalistically (Krajewski et al., 2018, Bärgman et al., 2017, Hankey et al., 2016, Mohammadi et al., 2023, Kalantari et al., 2023, Sun et al., 2023), on test tracks, or in driving/riding simulators (Mohammadi et al., 2023, Kalantari et al., 2023). Data for developing models of driver responses to critical events require much longer data collection times when collecting data naturalistically, as critical events are rare. However, data for developing models of crash causation to be used for scenario generation require even more data (longer collection duration and different method), as it is important to capture the prevalence and variability of the different crash causation mechanisms (Bärgman et al., 2023). Further, it is more difficult to develop both critical event response models and crash causation models based on test track and driving/riding simulators than it is to develop everyday driving models using the same study environments. The main reason is that the same drivers/riders have multiple exposures to the critical events: if drivers/riders are put in a situation where a conflict occurs on a test track or in a driving simulator, they are likely to behave substantially differently the next time they encounter critical

events during the same situation (Aust et al, 2013). Consequently, study designs need to be adapted accordingly, typically requiring substantially more participants, who require more overall study time (to include introductions, training, etc.). Further, test tracks and driving simulator studies cannot accurately represent the prevalence of crash causation mechanisms in real traffic, which is needed to make realistic safety benefit assessments of safety solutions that take exposure into account. Accurate exposure data must instead come from studies on the prevalence of crash causation mechanisms in the real world, which use several different methods (e.g., DREAM studies). These data are particularly rare for crashes involving vulnerable road users (e.g., cyclists and pedestrians).

In summary, in SHAPE-IT the initial plan was to develop and integrate the models needed for the virtual safety assessments of safety solutions for VRUs. However, it was soon clear that the difficulties in acquiring data on crash causation and critical events in naturalistic settings for car-to-crashes made it difficult to create such models. The PhD students instead developed everyday traffic-interaction models for car-to-VRU scenarios, which can be used in both ADAS/AD and as components in traffic simulation-based virtual safety assessments (Kalantari et al., 2022, Mohammadi, 2023, Yang, 2023, Zhang et al., 2023).

3.2 Computational load and simulation optimisation

Although using computer simulations to assess safety is far more efficient than running field-operational tests (Isaksson-Hellman & Lindman,2015, Wimmer et al. 2023), the time and resources needed to perform safety benefit assessments can still be substantial. One challenge is model complexity. When safety solutions are assessed and the developers/researchers merge complex computational models, they must carefully manage the computational loads so that the virtual simulation can still be be completed in a reasonable time. In both traffic and counterfactual simulations, multiple parameters are typically varied and sampled (often stochastically) to create a large set of potential conflict (or crash) situations. When using complex behaviour models, and/or multiple models for different road-users and different scenarios, the number of parameters may be huge. As the number of parameters increases and the number of distinct values to be simulated per parameter also increases, the number of permutations increases exponentially (Imberg et al., 2022, Feng et

al., 2020). It is not unusual to discover that, if all combinations of parameters and parameter values are to be simulated, the simulation's completion time can be counted in years. Research is still needed on how to design sampling strategies that are as efficient as possible (i.e., running as few simulations as possible), while making sure that the safety benefit estimates are as accurate and precise as possible (Imberg et al., 2022).

3.3 Software interoperability

Software interoperability is another challenge for computational model integration. Although it is more related to the practical integration of behaviour models in virtual safety assessments "in production" than to model integration for research purposes, its importance should not be underestimated. Virtual simulations may involve different programming languages and simulation platforms (i.e., simulation toolchains) even within a single organisation; differences across organisations are inevitable. Integrating computational behaviour models across different toolchains can be difficult due to compatibility issues, including differing data formats, interfaces, programming languages, units, and variable availability in the simulation environments. Standardisation work is needed to facilitate better model interoperability. Projects such as (V4SAFETY_consortium, 2023) are taking steps to address these interoperability issues.

Another aspect of software interoperability relates to the ways that different virtual assessment toolchains implement interaction models. How interaction details between road users are captured in the simulations can differ substantially. In virtual assessments, computational driver models interact with other simulated entities like pedestrians, other vehicles, and traffic infrastructure. Ensuring seamless interactions while eliciting realistic (and safe) behaviours adds complexity and limits the ease with which models can be shared and integrated.

Similarly, integrating behaviour models into virtual safety assessments requires seamless data exchange between the behaviour models and the simulation environment. Ensuring that data remain consistent and synchronised throughout the simulation is crucial for accurate results. As different toolchains require different formats and synchronisation, care must be taken when transferring a model (or set of models) from one toolchain to another.

4 Conclusions

The SHAPE-IT project gathered and/or obtained access to a wide range of road user data using car driving simulators, rider (bicycle) simulators and pedestrian simulators, as well as data from on-road (naturalistic) observations, such as road-side cameras and in-vehicle measurements.

Simulator data measured both behavioural and subjective aspects, such as feeling safe and accepting AVs. Simulator data is by nature limited in duration, and thereby less suitable for identifying (rare) crash causes. However, human behaviour, visual attention, physiology, and subjective aspects can be evaluated in simulators. Genuine road-user behaviour from naturalistic data included some critical events but no crash-related human state such as distraction or drowsiness was observed. This relates to the limited experiment duration, the instructions, and the rather eventful conditions.

The only on-road data in SHAPE-IT were limited to behaviour, although subjective evaluations can be conducted through in-vehicle studies. The on-road data included far more events than the simulator data, but still included few conflicts and no crashes. Moreover, human states such as intoxication, drowsiness, or distraction were not measured in the naturalistic data.

The ESRs who collected and analysed these data gathered valuable insights into human behaviour and acceptance of automated driving. Driver, rider and pedestrian models were developed with a focus on behaviour, and some models captured perceived risk and trust in AVs.

The behaviour models can be used to investigate and predict crash risk. However, as of today their integration in virtual simulations is not obvious because the models are not validated with respect to the crash causation mechanisms.

We must also reflect on the state of the art in highway traffic simulations. Simulations are often applied to address crash risk, but predictions are limited to trends, rather than absolute risk prediction. Surrogate safety metrics such as time to collision are used to identify critical interactions in relation to infrastructure design and vehicle automation. Where absolute crash

risk prediction remains an important target, trend prediction as studied in SHAPE-IT will already be of great value for AV-VRU interactions.

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