Hi-Drive

Designing Automation

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Research Questions

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Hi-Drive

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Executive Summary

In a large European project with more than 40 partners from different backgrounds, it is necessary to define the overall goals of the work early in the project. In Hi-Drive, this is partly done by defining the research questions that describe, at various levels of detail, the questions and challenges for which results are expected as an outcome of the project. Therefore, the overall goals need to be broken down to more detailed levels that can be directly linked, for instance, to data needs or specific working groups, operations, or experiments. As such, the research questions can guide and structure the work of the project.

The description of work served as a starting point to define the research questions for Hi-Drive. Based on this document, a list of six high-level research areas was defined covering the widespread overall goals of the project, as well as of the different subprojects. For each research area, research questions were derived and structured, starting from high-level questions related to separate research topics to low-level questions that can be linked to single studies or indicators. In this document, each research area is addressed in a dedicated chapter in which a state-of-the-art review and a list of related medium- and high-level research questions are presented.

Three of the research areas relate to the field of user evaluation and address user-related topics that are relevant for making automated driving an acceptable and easy to use technology. In detail, these user-related research areas address the topics of:

- Acceptance and comfort of automated driving (Chapter 3)
- Handling and use of automated driving systems (Chapter 4)
- Design of automated driving systems to ensure smooth interaction with other road users (Chapter 5).

The other three research areas are linked to effects evaluation. Two areas deal with the evaluation of the new technological solutions (enablers) to be developed in Hi-Drive. The enablers aim at making automated driving a less fragmented and more robust technology. The third area covers the field of impact assessment. Here, the potential impact of automated driving technologies after market introduction will be evaluated and, based on that, the societal benefit will be assessed. In detail, the research areas in the field of effects evaluation address the topics of:

- Effects of enablers on availability of automated driving (Chapter 6)
- Effects of automated driving and enablers on driving behaviour (Chapter 7)
- Impact of automated driving and enablers after market introduction (Chapter 8).

In total, 12 high-level and 44 medium-level research questions have been defined for user evaluation and 15 high-level and 34 medium-level questions for effects evaluation. The research questions lay the groundwork for further work in subproject 4 Methodology. They will be used to define the data requirements and experimental design and to develop detailed analysis plans for user evaluation and effects evaluation. Based on the methodological requirements, data will be collected for effects evaluation mostly in on-road tests on public roads or on test tracks, and dedicated user experiments and surveys will be run to answer the research questions for user evaluation. In the end, Hi-Drive will have addressed a wide range of challenges for automated driving based on the research questions and thus will pave the way for a successful development of automated driving.

1 Introduction

1.1 The Hi-Drive project

Connected and Automated Driving (CAD) has become a megatrend in the digitalisation and automation of society and the economy. CAD has the potential to drastically change transportation and to create far-reaching impacts. SAE level 3 (L3) (SAE, 2021) automated driving functions (ADFs) were piloted in Europe by the L3Pilot project in 2017–2021 (www.l3pilot.eu).

Hi-Drive builds on the L3Pilot results and advances the European state-of-the-art from SAE L3 'Conditional Automation' further up towards 'High Automation'. This is done by demonstrating in large-scale trials the robustness and reliability of CAD functions under demanding and error-prone conditions with special focus on:

- Connected and Automated vehicles (AVs) travelling in challenging conditions covering variable weather and traffic scenarios and complex infrastructure
- Connected and secure automation providing vehicles/their operators with information beyond the line of sight and on-board sensor capabilities
- Complex interaction with other road users in normal traffic
- Factors influencing user preferences and reactions including comfort and trust — and eventually through a wide consumer acceptance of automated driving (AD) resulting in purchase and use, enabling viable business models for AD.

The project's ambition is to extend considerably the CAD's operational design domain (ODD) from the present situation, which frequently demands taking over control of the vehicle by a human driver. As experienced in the EU flagship pilot project L3Pilot, on the way from A to B, a prototype AV will encounter a number of ODD factors, leading to fragmented availability of the ADF. Hi-Drive addresses these key challenges, which are currently hindering the progress of vehicle automation. The concept builds on reaching a widespread and continuous ODD, where automation can operate for longer periods, and the interoperability is assured across borders and brands. Hi-Drive strives to extend the ODD and reduce the frequency of the take-over requests (TOR) by selecting and implementing technology enablers leading to highly capable CAD functions, operating in diverse driving scenarios including, but not limited to, urban traffic and motorways. The removal of fragmentation in the ODD is expected to give rise to a gradual transition from conditional operation towards higher levels of AD. With growing automation, safety as well as experienced usability and comfort are expected to increase, which should result in increased acceptance by the user.

Testing and evaluation in Hi-Drive will focus on three areas: 1) users; 2) AD availability and performance; and 3) societal impacts (namely, the effect of AD on safety, efficiency, environment, mobility, transport system, and society). Furthermore, these assessments will serve as input to determine whether the socioeconomic benefits outweigh the costs. The project also engages in a broad dialogue with stakeholders and the general public to promote Hi-Drive results. Dissemination and communication are boosted by a demonstration campaign to show project achievements.

Overall, Hi-Drive strives to create a deployment ecosystem by providing a platform for strategic collaboration. Accordingly, the work includes an EU-wide user education and driver training campaign and series of Codes of Practice (CoP) for the development of ADFs and Road-Testing Procedures, while also leading the outreach activities on standardisation, business innovation, extended networking with interested stakeholders, and coordinating parallel activities in Europe and overseas.

1.2 Overall implementation plan for Hi-Drive

The FESTA methodology was designed to be applied to field operational tests with market-ready products (see Version 8 of the FESTA Handbook by Fot-NetCartre and Arcade (2021)). Therefore, it does not fully apply to studies with prototypical ADFs. Thus, some adjustment of the FESTA implementation plan, described as the "FESTA-V" structure, was needed to accommodate testing of AD.

Figure 1.1 presents the FESTA implementation plan adapted for Hi-Drive. The plan is divided into three phases: (I) prepare, (II) operate, and (III) evaluate. At the beginning of the preparation phase (I), ADFs and their technology enablers, as well as their use cases and associated test scenarios across multiple test environments (test track, open road, simulation, were described in detail. Then, in the draft version of this deliverable, an initial list of research questions was drawn up and organised as high-, medium-, and low-level questions. The state of the art was summarised for topics covered by these research questions. In this final version of the deliverable, the feasibility of each research question was checked with regard to data availability, suitability of the experimental design and procedures, availability of research tools, methods and external data sources, and availability of resources. Based on this feasibility check, a final list of research questions for implementation and testing in the project has been compiled.

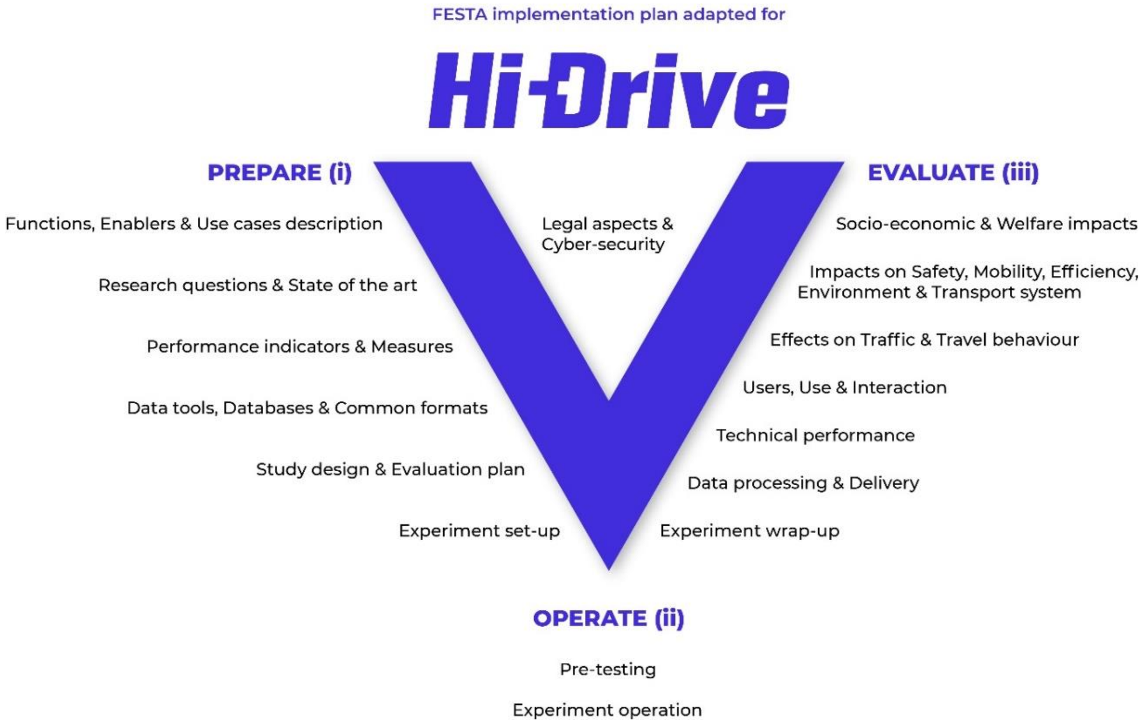

Figure 1.1: FESTA implementation plan adapted for Hi-Drive.

Next, the performance indicators and other data used for answering the research questions, as well as for calibrating the evaluation tools, are defined. Based on these requirements for evaluation, data logging requirements are defined and agreed with the partners to ensure that the data logged in the project is sufficient for answering the research questions. Furthermore, experimental design and procedures are planned for testing of highly AD and its technology enablers, and to provide data for evaluation. The plans for operation sites and experiments are approved between partners running the tests and the partners involved in setting the overall methodology for evaluation. Finally, an evaluation plan is set for each research question, specifying the methods, tools, and data to be used, scenarios to be addressed, and, where necessary, the definition of the baseline.

The operation phase (II) starts with the pre-testing step. It involves running all the phases of the project on a small scale to ensure that all the processes and tool chains function as intended. Once everything is confirmed to function as intended, the experiment operation begins. This phase involves the actual data collection, for instance on public roads, on test tracks, or in dedicated user studies like surveys.

The evaluation phase (III) starts with the data delivery as part of experiment wrap-up. In this phase, it is also important to report all the deviations from the plan and any system updates made during the data collection phase. Data is converted to a common data format, processed, and delivered to the evaluation team.

In the effects evaluation, technical performance of the tested technology (AD and advanced/enhanced AD with enablers) is assessed. The observed effects are scaled up and effects on traffic and travel behaviour are assessed and scaled up to European level together with their societal impacts on safety, mobility, efficiency, and the environment. The final step is to assess the socioeconomic and welfare impacts. In the user evaluation, dedicated user studies are planned that focus on users, use of AD, and interactions between AD and other traffic participants like vulnerable road users (VRUs).

1.3 Objective, scope, and structure of the deliverable

To achieve all this, input and contributions from many different partners are needed. Therefore, the overall work in Hi-Drive is structured into subprojects (SPs) that address predefined parts within the process leading to the final results. This deliverable is one outcome of SP4 *Methodology*. The objectives of the *Methodology* subproject (SP4) are to:

- Specify the Hi-Drive research questions for both users and effects evaluation, how they will be addressed, and related data needs.
- Agree on a common data format for provision of different datasets.
- Agree on experimental design and procedures for testing and evaluation of ADFs and related enablers in challenging environments.
- Reconsider the theoretical background and impact mechanisms to build a multidisciplinary evaluation methodology, covering not only the expected positive impacts on safety, comfort, and the environment, but also the unintended — possibly negative — impacts on users and the transport system.
- Refine the state-of-the-art methods to address user and human factor aspects of AD and facilitate understanding of possible effects on the transport system level, addressing travel behaviour, safety, efficiency, and emissions.
- Provide lessons learned from the methodology point of view.

This deliverable reports on the activities of the work package (WP) 4.3 Research questions. The purpose of the WP is to define the overall research questions of the project based on the overall goals of Hi-Drive described in the Description of Work (DoW) and the current state of the art. To reach this goal, the work of WP4.3 started early in the project and a draft list of research questions was generated in month 6 of the project (Dec. 2021). This draft version served as input to the other WPs in the methodology SP. In month 18 of the project (Dec. 2022), the final list of research questions was provided in this deliverable.

2 Definition of research questions

2.1 Process for defining the research questions

In a large European project with more than 40 partners from different backgrounds, it is necessary to define the overall goals of the work early in the project. In Hi-Drive, this was done by defining the research questions that describe, at various levels of detail, the questions and challenges for which results are expected as an outcome of the project. It is not sufficient that this is done on a high level; the overall goals need to be broken down to more detailed levels that can be directly linked, for instance, to data needs or specific working groups, operations, or experiments. As such, the research questions can guide and structure the work of the project.

The DoW served as a starting point to define the research questions for Hi-Drive. Based on this document, an initial list of six high-level research areas was defined that cover the overall goals of the project, as well as of the different SPs.

Specific research interests of the different partners were collected in greater detail by completing a common template on the plans of each partner and through workshops taking place for the different WPs. For instance, full-day workshops were organised for each WP of SP6 *Users*, where all involved partners presented their plans for Hi-Drive, stated the research areas and research questions they would like to address, and identified contact points for collaboration within the project.

In a subsequent step, the information collected on research interests was sorted and matched to the identified high-level research areas. Resulting detailed research questions were grouped based on their content, and higher-level research questions were developed that describe the overall goal of the grouped detailed research questions. In this way, a structure for sorting the research questions and research interests was developed, starting from the research areas and then moving from high-level to lower-level research questions. The overall goal of that work was that in the end, low-level questions are defined for all high-level research questions. On the lowest level, they need to be defined in such detail that either potential measurable performance indicators can be derived or they can be linked to specific research plans of dedicated partners.

Additionally, summaries of the current state of the art were written for the identified research topics, mainly by partners who already have profound expertise in the identified research areas and related subtopics. With this process, the identified research questions were mirrored against what is already known in the literature. As such, it is ensured that the work planned in Hi-Drive actually addresses research gaps and goes beyond the state of the art.

Furthermore, the state of the art helps to select the most appropriate measures and methods suited to achieve the goals of the project.

The derived list of research questions was presented in a draft version of this deliverable in December 2021. In spring 2022, the initial list of research questions was intensively discussed with various partners of the project with regard to content, structure, and wording. After various revisions, the research questions were checked for their feasibility within the project. Here, the focus was on the availability of data needed for analysing the research questions. This check of feasibility actively involved partners from other WPs of SP4 *Methodology*, SP5 *Operations* that actually runs the vehicle-based data collection, SP2 *Enablers* that sets the technology enablers for the AD, and SP6 *Users* that is responsible for dedicated studies on user related topics. Figure 2.1 shows a simplified process of the development of research questions. This deliverable reports the final list of research questions, and how these were refined after the feasibility checks. Furthermore, it includes the state-of-the-art reviews written during the process of refining the research questions.

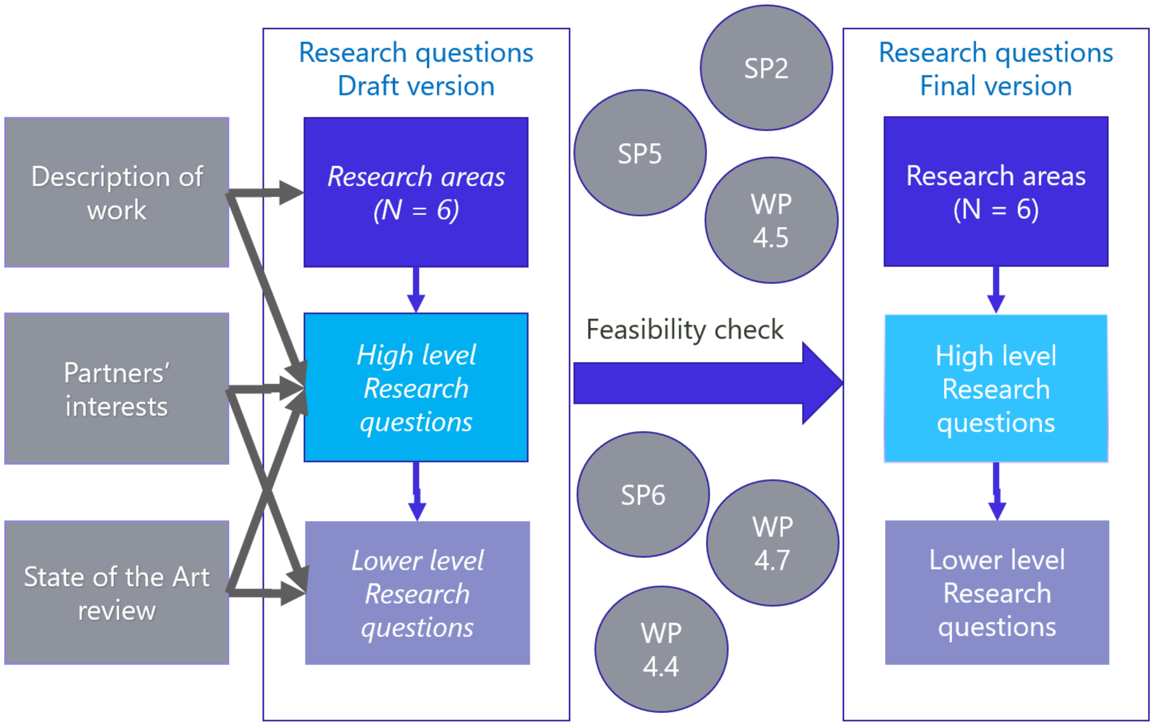

Figure 2.1: Simplified process of defining the research questions.

2.2 Answering the research questions

The six research areas can be assigned to the two main evaluation fields in Hi-Drive: user evaluation and effects evaluation. The research questions in three research areas belong to the field of user evaluation (see Table 2.1) and will mainly be addressed in SP6 *Users*. It is responsible for the implementation of user-related studies, collection of the required data, and analysis of that data.

In the area of effects evaluation, several SPs will be involved in the process of answering the research questions. This will start with SP2 *Enablers*, which is developing the technical solutions that enhance AD performance (the enablers) and will integrate them into the vehicles together with SP3 *Vehicles*. Then, these vehicles will be used by SP5 *Operations* to conduct the tests and collect the data. Based on that data, questions belonging to the field of effects evaluation will be answered by SP7 *Effects*. Going beyond the analyses for the research questions reported in this deliverable, there are detailed analyses planned in which the functioning of the developed enablers will be evaluated, specifically per enabler on a fine-grained, technical level. Since this work requires specialised knowledge of the implemented technologies, it will be done and reported as part of SP2 *Enablers*. Figure 2.2 shows the described process and the involved SPs.

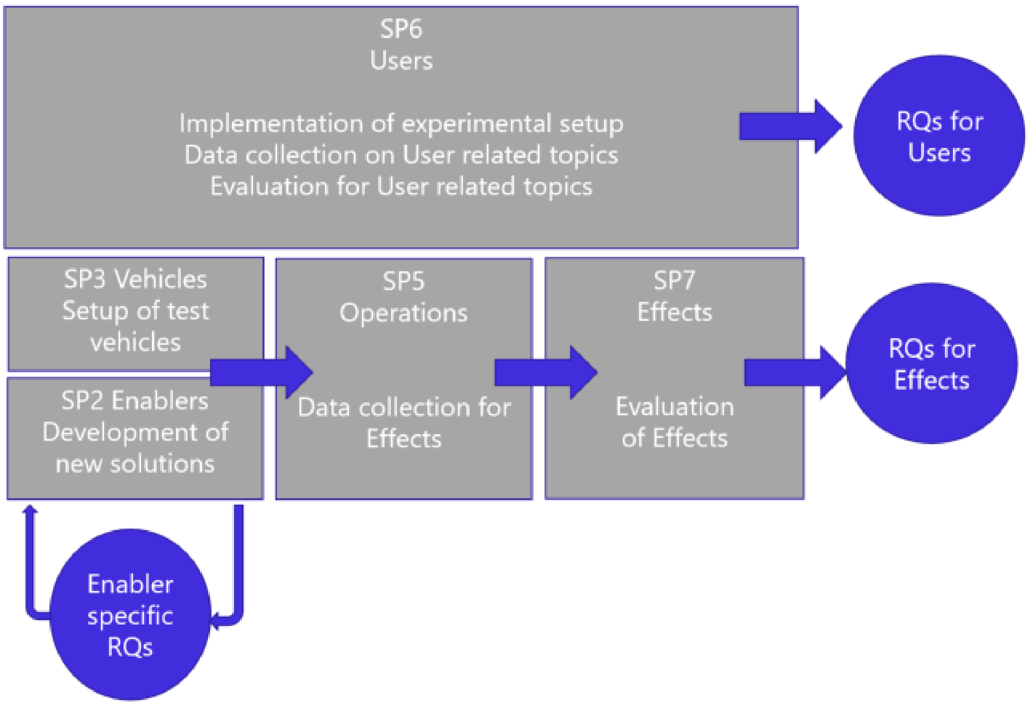

Figure 2.2: Planned process for answering the research questions for user evaluation and for effects evaluation.

2.3 Structure of research questions

The overall goal of Hi-Drive is to defragment and/or extend the ODD and make AD performance more reliable. This will help to make AD a safe, pleasurable, comfortable, acceptable, and widely used technology. All six high-level research areas (see Figure 2.3 and Table 2.1) address core challenges that need to be overcome to reach this aim. The six research areas can be assigned to the two main evaluation fields in Hi-Drive: user evaluation and effects evaluation. Figure 2.3 shows an overview over the six research areas.

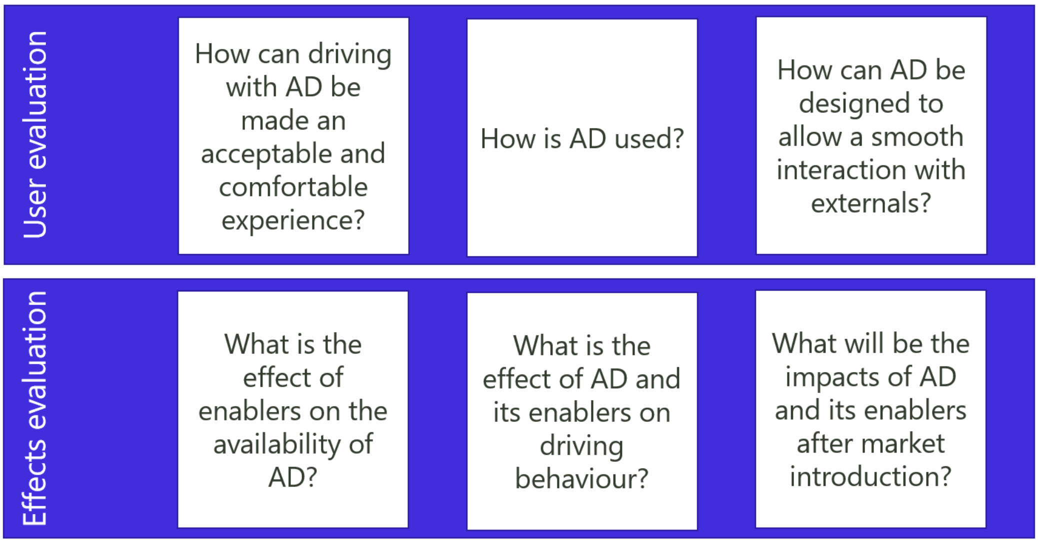

Figure 2.3: Overview of research areas in Hi-Drive.

Table 2.1 gives a more detailed content description of the six research areas. For the user evaluation, the three different research areas are linked to different user-related topics relevant for investigating evaluation and handling of AD by potential users, other traffic participants, or the general public. For the area of effects evaluation, the three identified areas relate to the planned testing of AD and its enablers within Hi-Drive. One of the main objectives of the project is to show how the integrated technology enablers improve performance within the ODD or extend the ODD of the ADFs. As described in the Use case/Test scenario catalogue deliverable, D3.1 (Bolovinou et al., 2022), two sub-types of ODD specification have been considered for testing the integration of enabler technologies:

- The nominal ODD for testing the driving behaviour while driving with AD in which the effect of AD on driving behaviour can be analysed and
- An extended ODD for testing "AD availability", where additional challenging operating conditions are tested in order to assess AD robustness under conditions falling beyond the nominal ODD of the ADF under test.

Following this differentiation, research questions for analysing Hi-Drive technical effects are clustered into research questions on AD availability and research questions on the effect of AD on driving behaviour. The third area deals with upscaling of the effects identified in the other research areas to the traffic network and estimating the potential impacts of AD for society (impact assessment).

In this deliverable, high- and medium-level research questions are reported for each research area. Furthermore, a description of the state of the art for the high-level research questions is provided. However, internally, the medium-level research questions are broken down further to low-level research questions and partly further down to sub-questions. The questions on the lowest available level are either linked to performance indicators for questions addressing the effects evaluation or to single experiments or surveys planned in the field of user-related studies. Table 2.2 shows some examples from the field of effects evaluation of how high-level research questions are broken down to low-level ones and how those are linked to performance indicators. That approach of structuring the research questions for the whole project follows the approach already successfully implemented in L3Pilot (L3Pilot Deliverable 3.1; Hibberd et al., 2018).

In the following sections, these six research areas are addressed in separate chapters, always giving an introduction to the topic together with a state-of-the-art review. Then, the high-level and medium-level research questions are listed for this research area.

Table 2.1: Content of the six research areas. In the column "Chapter", the number of the chapter is given in which more detailed information on the research area is provided.

	Research Area	Goal of the work	Chapter
User evaluation	How can driving with AD be made an acceptable and comfortable experience?	AD will only become widely used if it is deemed acceptable, safe, and comfortable. In this research area, the views and interactions of the general public, but also of drivers who have experienced AD, will be evaluated. Furthermore, aspects known to make AD less acceptable for at least some users are addressed. These include motion sickness, which is closely related to the experience of driving comfort. The results of this work can be used to better understand how to make AD a widely accepted technology.	3
	How is AD used?	Besides being able to manage the driving task in a safe and reliable way, AD needs to be designed such that it can be used safely and easily by non-expert drivers. For this, we need to understand how ordinary drivers use AD, e.g., how they would like to spend their time driving with AD, how AD impacts the drivers' state and their behaviour, and how a safe handling of AD (e.g., in situations where the driver takes back control) can be ensured. Here, one specific challenge is to ensure, for instance through driver monitoring, that the driver is in a state in which they are able to take back vehicle control, if required to do so. Furthermore, this research area goes beyond users inside the vehicle (drivers) and includes users handling a vehicle from outside the vehicle, via teleoperation.	4
	How can AD be designed to allow a smooth interaction with externals?	To be successful in everyday traffic, AD will need to work efficiently and safely within a complex traffic environment. This does not only require that AD manages its ODD safely but also a safe and smooth interaction with other traffic participants. This research area will investigate how the interaction of AVs with other traffic participants can be improved and made safe, smooth, acceptable, and efficient. The focus of the work will be on the perspectives of other road users like pedestrians, cyclists, or other drivers.	5

	Research Area	Goal of the work	Chapter
Effects evaluation	What is the effect of enablers on the availability of AD?	Current AD solutions still frequently face situations which the AD cannot handle and that therefore result in a TOR. In the project, these challenges are addressed, and enablers are developed and tested that will make driving with AD feasible in currently challenging situations (e.g., bad weather conditions or challenging infrastructure) previously outside the ODD. The aim is to allow a more robust and less fragmented availability of AD. In this research area, the developed enablers will be tested on the level of AD and their impact will be evaluated with regard to the measurable availability and robustness of AD.	6
	What is the effect of AD and its enablers on driving behaviour?	To understand the potential effects of AD on driving, it needs to be understood how AD impacts driving behaviour not only in simple driving scenarios but also in complex driving environments. This research area does not only relate to the effect of AD on the behaviour of the vehicle equipped with ADF but also to the measurable effect on the behaviour of surrounding traffic. Therefore, the effect of AD on measurable driving behaviour is analysed and described based on vehicle data collected within the project.	7
	What will be the impacts of AD and its enablers after market introduction?	This research area addresses the field of impact assessment, where effects of AD observed in experiments or on-road tests are scaled up to a higher level. To evaluate the benefits of AD for society, the impact of AD on overall traffic safety and efficiency but also environmental impacts and impacts on mobility and the road transport system need to be understood and quantified. In this research area, potential scaled-up impacts of AD and of the implemented enablers will be assessed and evaluated. This will then be used to estimate the societal impact of AD. Based on the work of this research area, the potential societal impacts of AD will be described.	8

Table 2.2: Example of the relation between research questions and performance indicators. TOR = Take-over request; N = number of; THW = Time headway; lat. = lateral; long. = longitudinal; acc. = acceleration; std = standard deviation; max = maximum; abs.= absolute value.

Research Area	High level	Medium level	Low level	Performance indicator
What is the effect of enablers on the availability of AD?	To what extent do the enablers extend the ODD?	To which environmental conditions do the enablers extend the ODD?	-	%scenario instances w/o TOR
		To which road infrastructure elements do the enablers extend the ODD?	-	%scenario instances w/o TOR
	To what extent do enablers enhance AD robustness?	To what extent do enablers enhance AD robustness in challenging environmental conditions?	-	N(TOR)/scenario
		To what extent do enablers enhance AD robustness in challenging road infrastructure conditions?	-	N(TOR)/scenario

Research Area	High level	Medium level	Low level	Performance indicator
What is the effect of AD and its enablers on driving behaviour?	What is the effect of AD and its enablers on safe driving behaviour?	What is the effect of AD and its enablers on the frequency of incidents?	What is the effect of AD and its enablers on the frequency of close distances to other traffic participants?	N(THW<Threshold) /scenario
			What is the effect of AD and its enablers on the frequency of emergency brakings?	N(long.acc<Threshold) /scenario
	What is the effect of AD and its enablers on comfortable driving behaviour?	What is the effect of AD and its enablers on lateral acceleration?	What is the effect of AD and its enablers on the variation of lateral acceleration?	std(lateral acc.)
			What is the effect of AD and its enablers on the maximum lateral acceleration?	max(abs(lateral acc.))
		What is the effect of AD and its enablers on longitudinal acceleration?	What is the effect of AD and its enablers on the variation of longitudinal acceleration?	std(long. acc.)

3 User Evaluation – Acceptance and comfort

3.1 Scope of this research area

The first research area of user evaluation covers a range of research topics related to the acceptance and acceptability of AD. Acceptance and a positive attitude towards AD by the general public are relevant for a successful deployment of AD on the market (Zhang et al., 2019b).

Within this research area, the terms *acceptance* and *acceptability* are used regularly, and it is therefore important to highlight the difference between them. Most individuals have certain expectations from or attitudes towards AVs without having experienced them in real life. This is referred to as *acceptability*, a prospective judgement about such systems. *Acceptance*, in contrast, describes attitudes towards the system after having experienced it. This experience can occur, for instance, in user studies using driving simulators, a Wizard of Oz, or a prototype vehicle. Acceptability does not necessarily lead to acceptance after using the system, and conversely, a lack of acceptability before the first encounter does not necessarily mean that users will reject the system after experiencing it (Jamson, 2013). *Trust* in automation is considered to be a key premise for the use and acceptance of AD (Kyriakidis et al., 2017). The initial attitude towards AD or the acceptability of AD is likely to change when drivers actually experience it. If drivers are subjected to critical situations when using the system, their trust in and thus acceptance of AD decreases (Gold et al., 2015). Therefore, repeated experience of system boundaries can affect the driver’s trust and acceptance of AD. Furthermore, *comfort* and car sickness are identified as relevant factors for the acceptance of AD.

The next section provides more detail of the state of the art in acceptance and acceptability, followed by identification of the research gaps in this area.

3.2 State of the art

3.2.1 Acceptance, acceptability, and related constructs

Research in the field of automated vehicle acceptance has grown tremendously in the past few years. Online surveys and interview studies have shown a substantial variance in the intention to buy and use automated vehicles within and between populations. In a 2012 survey with 17,400 vehicle owners in the United States, 37% showed interest in buying a vehicle with AD capacity (Power, 2012). Another survey with nearly 5,000 respondents from 109 countries asked about their attitudes towards AD and found that AD was rated as easier than manual driving, but also as less enjoyable (Kyriakidis, Happee and De Winter, 2015).

In human factors research, it is known that the acceptance and usage of a technical system is related to various constructs:

- The perceived usefulness of AD for the user might increase with an increasing automation level. When drivers are not required to monitor the system's performance and are allowed to engage in other activities, they might perceive the system as more useful. Several surveys have been conducted on the non-driving related tasks (NDRTs) drivers want to engage in while driving in automated mode. The perceived usefulness of the AD depends on the extent to which drivers are able to perform these NDRTs (Naujoks, Wiedemann and Schömig, 2017).
- A positive effect of perceived ease of use on perceived usefulness has been supported by the literature on automated vehicle acceptance (Herrenkind et al., 2019, Nordhoff et al., 2020b, Zhang et al., 2019b), which is in line with the broader body of research on technology acceptance (Adams, Nelson and Todd, 1992, Karahanna, Agarwal and Angst, 2006, Venkatesh and Davis, 2000).
- Trust is a key variable for the use of AD (Lee and See, 2004). The driver's level of trust in the AD not only influences the overall usage, it also influences the driver's state while using the system: Studies suggest that high trust in AD is linked to higher levels of drowsiness (Kundinger, Wintersberger and Riener, 2019) and higher engagement in NDRTs (Kyriakidis, Happee and De Winter, 2015). An unreasonably high level of trust can lead to drivers neglecting their monitoring duties or poor take-over performance.
- The (perceived) safety of an AD is a key factor for its safe usage. If drivers do not perceive the system as safe, they will not trust it. And if drivers do not trust the automation, they will not use it (disuse; Parasuraman and Riley, 1997). Perceived safety was found to predict the perceived reliability of the system and, finally, the acceptance of AD. On the other hand, if drivers over-rely on the automated system, this might lead to decision errors, for example, in terms of not responding appropriately to TORs. Several authors have suggested that perceived safety results in the matching of continuous anticipatory monitoring with the driver's expectations, and that another process occurs when a mismatch, or perceived risk, occurs: the driver perceives and assesses a risk to determine whether or not it is negligible (Näätänen and Summala, 1974, Tanida and Pöppel, 2006).
- Trust is closely tied to the perceived reliability of an automated system. If the perceived reliability increases, trust is likely to increase as well. In a survey of 109 users of Tesla's Autopilot conducted by Dikmen and Burns (2017), initial trust (referring to acceptability) was compared to the level of trust after a certain period of use. Trust in the system was

positively correlated with frequency of use, knowledge about the system, ease of use, and perceived usefulness of the Human-Machine Interface (HMI).

Modelling acceptance and acceptability

Studies have predicted AD acceptance as a function of direct and indirect factors from common technology acceptance models, applying bivariate correlation, regression, or structural equation analyses (Lee, Baig and Li, 2022, Xu et al., 2018, Zhang et al., 2019b, Zhu, Chen and Zheng, 2020) . One well used technology acceptance model is the Unified Theory of Acceptance and Use of Technology (UTAUT; Venkatesh et al., 2003). The UTAUT integrates eight influential acceptance models, including the Theory of Planned Behaviour (TPB; Ajzen, 1985) and the Technology Acceptance Model (TAM; Venkatesh and Davis, 2000). UTAUT assumes that an individual's behavioural intention to use a technology is influenced by various factors, such as performance expectancy, effort expectancy etc. (i.e., degree to which the individual believes they possess the resources to use the technology; Venkatesh et al., 2003). As the original UTAUT model was tailored to the organisational context, UTAUT2 was developed to look at other contexts. UTAUT2 posits that, in addition to the UTAUT constructs, the intention to use a technology is influenced by hedonic motivation, price value, and habit (i.e., defined as the passage of time from the initial technology usage; Venkatesh, Thong and Xu, 2012).

A wide range of studies have addressed the acceptance and acceptability of private conventional and public pod-like automated vehicles, applying constructs from common technology acceptance models such as the TAM, TPB, and UTAUT (Kaur and Rampersad, 2018, Kaye et al., 2019, Madigan et al., 2016, Madigan et al., 2017, Rahman et al., 2017, Xu et al., 2018, Zhang et al., 2019b, Zhang et al., 2020). Overall, these studies show that intention to use a L3AD is determined by:

- perceived usefulness (Xu et al., 2018, Buckley, Kaye and Pradhan, 2018, Kaye et al., 2019, Zhang et al., 2019b, Zhang et al., 2020, Kaur and Rampersad, 2018, Madigan et al., 2016, Madigan et al., 2017),
- perceived ease of use (Xu et al., 2018, Kaye et al., 2019, Zhang et al., 2019b, Zhang et al., 2020, Kaur and Rampersad, 2018, Madigan et al., 2016, Madigan et al., 2017),
- perceived behavioural control (Buckley, Kaye and Pradhan, 2018, Kaur and Rampersad, 2018, Madigan et al., 2016, Madigan et al., 2017), and
- subjective norms (Buckley, Kaye and Pradhan, 2018, Kaye et al., 2019, Madigan et al., 2016, Madigan et al., 2017, Acheampong and Cugurullo, 2019).

Impact of user characteristics

Nordhoff et al. (2020b) suggest that the intention to use AD is lower for elderly people and females compared to younger age groups or males. In another study (Nordhoff et al., 2021), the gender differences were inconsistent, with males being more enthusiastic towards conditionally automated cars (SAE level 3), for the majority of countries studied. These findings mirror the literature on AD acceptance in two substantial ways. First, they correspond to studies which have shown significant, yet small, effects of age and gender on the factors predicting automated vehicle acceptance (Kettles and Van Belle, 2019, Kyriakidis, Happee and De Winter, 2015, Nordhoff et al., 2018). Second, the findings corroborate the more positive attitudes of males than of females towards automated vehicles, as shown through higher ratings of perceived usefulness, social norms, and trust, which reflects a relatively consistent pattern across studies on automated vehicle acceptance (Rahman et al., 2017, Rice and Winter, 2019).

Nordhoff et al. (2020b) also revealed small positive effects of experience with advanced driver assistance systems on the intention to use L3-AD. This corresponds to the report by KyriakidisHappee and De Winter (2015) that people who currently use Adaptive Cruise Control (ACC) would be willing to pay more for automated vehicles, and are more comfortable about driving without a steering wheel. Other studies investigated the relation between experience with Parking Assist systems and the intention to use AD (Trösterer et al., 2014, Baldock et al., 2006), but with mixed results.

Other research in this context has clustered users on the basis of certain characteristics, for instance their enthusiasm/scepticism towards automated cars, their attitudes towards the future use of AD on public roads, likelihood of purchasing a personal and shared automated/driverless car, awareness/knowledge about automated cars, or the perceived benefits and concerns about automated cars (Hardman, Berliner and Tal, 2019, Hulse, Xie and Galea, 2018, Liu, 2020, Nielsen and Haustein, 2018, Pettigrew, Dana and Norman, 2019). These clusters have been given different names such as attitudinal groups with a positive, negative, ambivalent, or indifferent attitude (Liu, 2020), such as Laggards and Pioneers (Hardman, Berliner and Tal, 2019). Other terms used include: Likely Adopters and First Movers (Pettigrew, Dana and Norman, 2019) or Sceptics, Indifferent, and Enthusiasts (Nielsen and Haustein, 2018). Results suggest that sceptics were more concerned about AD and less enthusiastic than indifferents and enthusiasts (Nielsen and Haustein, 2018). Based on such results, barriers to the acceptance of L3-AD can be identified and user-group-specific strategies and appeals could be developed (see Laroche, Bergeron and Barbaro-Forleo, 2001, Pettigrew, Dana and Norman, 2019, Nielsen and Haustein, 2018). In order to fulfil the potential of AD, it is important to gain an understanding of the attitudes of different user groups so that researchers and automotive manufacturers can address concerns and deliver the benefits of automated cars to their customers.

Cross-national differences

Various studies have shown cross-national differences in the awareness, user experience, acceptance, perceived comfort, and attitudes towards AD, as well as willingness to pay, and acceptance of the AD's decisions (Ansys, 2019, Bellone et al., 2021, Edelmann, Stümper and Petzoldt, 2021, European Commission, 2020, Kaye et al., 2020, Lee, Baig and Li, 2022, Potoglou et al., 2020, Schoettle and Sivak, 2014a, Schoettle and Sivak, 2014b, Schrauth et al., 2020). Moody, Bailey and Zhao (2020) revealed that country-level awareness of AD was positively related to Gross Domestic Product (GDP) per capita, suggesting that respondents from economically developed countries were more aware of AD than others. A report of the European Commission (2020) has shown that respondents from the Netherlands, Sweden, and Denmark were most aware of AD, while respondents from Poland, Romania, and Bulgaria were least aware. According to Schrauth et al. (2020), respondents from Spain, Sweden, and Slovenia regarded the introduction of L3-AD as most beneficial, while those from Germany, France, and the U.S. found it least useful.

Louw et al. (2021) investigated the intention to use ADFs in one of four ODDs: Motorways, Traffic Jams, Urban Roads, and Parking. Intention to use was high across all these ODDs, but significantly higher for Parking than all others. The authors found that, overall, intention to use was highest amongst respondents who were younger (<39 years), male, and had previous experience with Advanced Driver Assistance Systems (ADAS). However, these trends varied widely across countries and for the different ADFs. Respondents from countries with the lowest GDP and highest road death rates had the highest intention to use all types of AD, while the opposite was found for countries with high GDP and low road death rates Louw et al. (2021). These results suggest that development and deployment strategies for AD may need to be tailored to different markets to ensure uptake and safe use.

3.2.2 Comfort during automated driving

One of the major factors likely to affect the acceptance of automated vehicles is the level of comfort which users feel while travelling in them (Arndt, 2011). However, comfort is a difficult concept to quantify, with numerous definitions existing in the literature. For example, Slater (1985) defines it as "a pleasant state of physiological, psychological and physical harmony between a human being and the environment", while Bellem et al. (2016) depict comfort as "a state which is achieved by the removal or absence of uneasiness and distress".

Although there is currently no agreement upon the definition of comfort in the AD domain, three commonalities have been identified anyway: comfort is (1) a subjective construct, (2) influenced by physical, physiological, and psychological elements, and (3) results from interaction with the environment (De Looze, Kuijt-Evers and Van Dieen, 2003). In addition, all the definitions describe comfort as a positive valence involving pleasantness, well-being, relaxation, and ease; whereby stress and uneasiness should be absent.

Discomfort, a concept considered to be the opposite of comfort, has also been defined, and is considered easier to measure compared to the weak, unaroused nature of comfort (Siebert et al., 2013). Discomfort has been considered as "a subjective, unpleasant state of driving-related psychological tension or stress in moments of a restricted harmony between driver and environment" (Hartwich, Beggiato and Krems, 2018), with specific emphasis on how this tension and stress originate from "unexpected, unpredictable or unclear actions of the automated system."

Comfort and discomfort can be projected in a schematic map of driving moods, defined by two "pleasant/unpleasant" and "activation level" axes (Russell and Barrett, 1999). Comfort is associated with a pleasant feeling of control or of insertion within the flow, when everything is going well. Discomfort was proposed to occur when drivers are not able to maintain the satisfying state of various control measures such as conditions of the trip (acceleration, thermal, visual …), rule following (to avoid a fine and social judgement), progress of the trip, or safety margins related to perceived safety (Summala, 2007).

Various methods have been used to measure comfort. Questionnaire measures include single ratings of how comfortable the driver feels, using a Likert scale (e.g., Bellem et al., 2017). A handset tool was provided to participants in a simulator to continuously indicate their level of discomfort through pressure on a trigger (Rossner and Bullinger, 2019, Hartwich, Beggiato and Krems, 2018). Interviews have also been used as a subjective measurement tool to investigate driving comfort (e.g., Basu et al., 2017). Objective measures include physiological metrics, which provide information reliably and in real time without annoying and distracting the driver (Radhakrishnan et al., 2020). However, to date, physiological measures have only been used to measure discomfort (for example, heart rate as an indicator of discomfort; Beggiato, Hartwich and Krems, 2019) because of the close relationship between characteristics of discomfort (i.e., stress and tension) and physiological indicators (Beggiato, Hartwich and Krems, 2019).

A number of concepts and factors are associated with comfort or discomfort. (e.g., Hartwich, Beggiato and Krems, 2018, Siebert et al., 2013). Other feelings that are considered to reflect comfort were measured as a part of discomfort, including nausea (Paddeu, Parkhurst and Shergold, 2020) and motion sickness (Bellem et al., 2018), or as a part of comfort, such as trust in automation (Bellem et al., 2018) and perceived safety (Rossner and Bullinger, 2019).

There are a range of factors that influence driver comfort. These include:

- Physiological factors, e.g., noise, vibration, and harshness (Qatu, 2012)
- Environmental factors, e.g., air quality and temperature (Da Silva, 2002)
- Vehicle movement patterns (Diels and Bos, 2016, Elbanhawi, Simic and Jazar, 2015)
- Naturalness of driving style (Elbanhawi, Simic and Jazar, 2015)
- Motion sickness (Elbanhawi, Simic and Jazar, 2015)
- Road and load disturbances (ElbanhawiSimic and Jazar, 2015)
- The individual's expectations of the context (Constantin, Nagi and Mazilescu, 2014)
- Perceived safety and trust (Bellem et al., 2018, Paddeu, Parkhurst and Shergold, 2020, Summala, 2007).

Implementing a desirable automated driving style is regarded as the primary means of prompting a comfortable experience for passive drivers, provided that the passengers' experienced comfort is largely determined by the driver's driving style in a manually driven car (Bellem et al., 2018). Thus, identifying what driving style is perceived as comfortable will be crucial for AV development and its broad adoption. This is likely to include a consideration of both smooth driving patterns and of drivers' expectations, as there are likely to be individual differences in preferred driving styles (Hartwich, Beggiato and Krems, 2018). Interestingly, research by Basu et al. (2017) comparing four different automated driving styles has shown that most drivers prefer a more defensive driving style than their own, regardless of their own manual driving style. This suggests that drivers may not actually perceive their own manual driving style as "natural", although there is still much room for research in this area, with some contradictory findings emerging (e.g., Griesche et al., 2016).

3.2.3 Car sickness

By taking on the role of a passenger in higher level AD (SAE L3 and up), the driver can engage in a variety of NDRTs during AD such as reading, working, watching videos, etc.— although only temporarily and until a TOR is required for L3, but for longer durations in L4 (SAE, 2021). However, engagement in tasks drawing visual attention away from the driving scene is thought to increase the risk of experiencing car sickness (Diels et al., 2016, Diels and Bos, 2016). Lack of control over the movements of the vehicle, and consequently the inability to anticipate the next manoeuvre of the AD, further increases the susceptibility to car sickness (Rolnick and Lubow, 1991). As a result, productivity and comfort while driving in automated mode may be reduced, limiting the benefits of AD and likely its acceptance (Diels and Bos, 2016, SmythJennings and Birrell, 2019).

Motion sickness, which is a natural response to a mismatch between perceived and real motion, is a well-known and long-acknowledged phenomenon that occurs not only in cars, but also in many kinds of transportation such as ships and aeroplanes (Tyler and Bard, 1949). There are different theories as to the origin of motion sickness, although no approach has been able to explain all aspects of the phenomenon. The most widely held theory is the sensory-conflict theory, which postulates that motion sickness occurs when there is a conflict between sensory inputs, i.e., the visual, vestibular, and non-vestibular systems including proprioception (Claremont, 1931). The theory of sensory rearrangement adds that the symptoms increase when the actual visual and vestibular impressions differ from the expected ones (Held, 1961). The predominant symptom of motion sickness is nausea, which in extreme cases leads to vomiting (Golding, 2016). Typically, however, nausea is preceded or accompanied by a number of other symptoms like sleepiness, apathy, burping, (cold) sweat, pallor, headache, or dizziness (Graybiel et al., 1968, Reason and Brand, 1975).

There is huge variability between subjects in terms of the appearance, order, and strength of symptoms (Diels and Bos, 2016). Women seem to be more susceptible than men to motion sickness (Brietzke et al., 2021, Flanagan, May and Dobie, 2005, Klosterhalfen et al., 2005, Paillard et al., 2013). However, some studies have not found this difference, suggesting a higher willingness to report motion sickness symptoms among women as a possible explanation for the supposed gender difference (Cheung and Hofer, 2002, Park and Hu, 1999). Furthermore, some studies have found that susceptibility increases with age, peaking in youth and decreasing subsequently (Bos et al., 2007, Brietzke et al., 2021, Lamb and Kwok, 2015), whereas a linear relationship of age, with younger subjects being more susceptible, has been found in other studies (Schmidt et al., 2020, Turner, 1999). As the occurrence further depends on several factors like means of transport, duration, and intensity of provocation (driving on a curvy road vs. driving on a motorway) but also on the engagement in different NDRTs, it is difficult to make statements about the general prevalence of this condition (Mühlbacher et al., 2020, Schmidt et al., 2020). It is therefore of interest to study the prevalence of car sickness while engaging in different activities under different conditions (road types, seating positions, etc.) in the general population. The results could indicate whether car sickness presents a relevant problem for society and whether this will be exacerbated by AD.

Fundamental studies (e.g., using off-vertical axis rotation) have shown that one of the main modulating factors seems to be the frequency of accelerations, with frequencies of 0.16 to 0.2 Hz being the most provocative (Dai et al., 2010, Donohew and Griffin, 2004, Griffin and Mills, 2002). The ISO 2631 document (ISO, 1997) describes the "Motion sickness dose value" as a calculation based on accelerations that predicts the intensity of motion sickness.

However, the predictive capability of this indicator is limited, and other factors like individual susceptibility should be taken into account (Brietzke, Pham Xuan and Bullinger, 2020, ISO, 1997). Besides driving dynamics, the influence of new propulsion technologies such as battery electric vehicles and different activities (e.g., reading, working, but also entertainment) on motion sickness are of interest.

Some recent studies focus on the influencing factors of car sickness, as well as on possible countermeasures. The factors mentioned include head position, posture, visual conflict, or anticipation (Bohrmann and Bengler, 2019, Brietzke et al., 2021, Kuiper et al., 2019, Saruchi et al., 2020). Potential countermeasures investigated to date include anticipatory cues, vibration, or airflow (D'amour, Bos and Keshavarz, 2017, Kuiper et al., 2020, Yusof et al., 2020). The methodology of these studies concerning e.g., the provocation of motion sickness or duration and type of drive are not consistent. In addition, most of the studies concerning motion sickness are fundamental research studies, yet a standardised methodology for driving studies to investigate car sickness in a replicable way is lacking (Mühlbacher et al., 2020). A consistent study design is therefore essential to develop, allowing the comparison of different countermeasures to enable maximum comfort while driving with AD. This includes, among other things, alignments on how to design a representative test track, how long the drive should last, which NDRTs should be employed to provoke car sickness, and how to identify susceptible participants.

Motion sickness not only decreases comfort, it has been shown to interfere with the performance of cognitive and physical tasks (Bos, 2004, Colwell, 2000, Stevens and Parsons, 2002). Regarding AD, the question therefore arises about the extent to which car sickness affects take-overs and driving performance when vehicle control has to be taken over, for instance in an emergency situation.

3.3 Overview of research questions

Based on the presented state-of-the-art literature research, research gaps were identified and research questions concerning the acceptability and acceptance of AD were formulated. This will include attention to some methodological challenges, especially in the fields of acceptance and acceptability and relating to car sickness. An overview of high- and medium-level research questions is given in Table 3.1.

Table 3.1: Overview of research questions on acceptability, acceptance, and comfort.

High-level research question	Medium-level research question
What is the attitude towards AD?	What is the willingness to pay for AD?
	What is the acceptability (acceptance before usage) of AD?
	What does the general public know about AD?
	What does the general public expect from AD?
	How does AD change the travel experience?
	What is the perceived safety of AD?
	What is the acceptance of AD by the user?
How can driving with AD be made a comfortable experience?	Which guidelines for automated driving behaviour can be derived from manual driving to make driving with AD more comfortable?
	What is the impact of driving style of AD on driving comfort?
	What is the impact of driving comfort on acceptance, trust, and other related concepts?
What is the impact of car sickness on the user?	With which methodological approach can car sickness be investigated in an efficient and replicable way?
	What is the prevalence of car sickness in the European population?
	How can the occurrence of car sickness be predicted?
	How can car sickness be reduced?
	How do NDRTs influence the incidence of car sickness?
	How does car sickness affect manual driving and take-over performance?

4 User Evaluation – Use of AD

4.1 Scope of this research area

The next user-related research area deals with the use of AD by the driver or the handling of AD by a teleoperator. The aim of this work is to understand how, after market introduction, ordinary drivers will handle, understand, and interact with the new ADFs, and which factors will influence this. Relevant situations include handling and use of AD while being in the ODD and at ODD boundaries e.g., when a TOR occurs. Studies addressing research questions in this area mainly observe how drivers behave and react before, during, and after they have an AD available.

Furthermore, in this research area the focus is widened and addresses not only drivers who are in the car but also teleoperators who handle an AV remotely, for instance at ODD boundaries. Based on the DoW and the state-of-the-art review, a wide range of topics was identified. For all these topics, research questions are defined that will be addressed within Hi-Drive.

4.2 State of the art

4.2.1 Human factors of transitions of control in automated driving

Although the classic aim of introducing automation to a system is typically to replace human manual control, Bainbridge (1983) argues why completely replacing human manual control may not be possible. One of the "ironies of automation" presented in the paper is that the tasks that are typically easy to automate get automated, while the tasks that are difficult to automate are often left for the human to handle. In other words, many automated systems can only operate under standard conditions, but need human intervention in more complex or difficult conditions (Bainbridge, 1983). This irony of automation becomes relevant when automation is increasingly introduced to passenger vehicles. Instead of replacing human manual control completely, the next generation of driving automation will rather change the tasks and the role of the driver compared to manual driving. Higher level AD promises to handle the driving task such that the driver does not need to supervise the system. However, a TOR is issued to the driver whenever the AD reaches its functional limits. Experts have identified these transitions of control as one of the major human factors challenges of AD (Kyriakidis et al., 2017). The drivers are seen to (physically and mentally) disengage from the driving task, which leads to diverted attention, lower situation awareness (Endsley, 2018, Merat et al., 2019), and fatigue (Naujoks et al., 2018a, Vogelpohl et al., 2019). Yet, when AD encounters functional limits, the driver is required to respond to the TOR in a timely and appropriate manner.

Numerous studies have been conducted in virtual environments (driving simulators of different fidelities) to investigate the driver's ability to safely resume manual control in response to a TOR. Drivers' response to TORs has mainly been assessed using a single take-over time (Mcdonald et al., 2019, Zhang et al., 2019a). The take-over time is typically defined as the time from a TOR until drivers have deactivated automation through a button press, steering, or braking. However, some studies also include response times to capture other parts of the response process to a TOR, such as the time to redirect the gaze towards the forward road or the time to place the hands on the steering wheel or the feet on the pedals (Gold et al., 2013, Eriksson and Stanton, 2017, Zeeb et al., 2017, Pipkorn et al., 2021, Pipkorn, Tivesten and Dozza, 2022).

A literature review by Eriksson and Stanton (2017) showed a great variance of 2–15 sec in drivers' take-over times in response to a TOR. Further, Zhang et al. (2019a) found mean take-over times to range from 0.69 sec up to 19.79 sec, with a mean take-over time of 2.72 sec. Take-over times have been shown to depend on driver characteristics, system characteristics, and situational variables. For example, Zhang et al. (2019a) found, in their meta-analysis of 129 take-over studies, that take-over times increase when drivers are engaged with a hand-held device, when they are visually distracted, and when they have no experience with take-over situations. Also, the modality of the TOR (i.e., the information type used in the TOR procedure, e.g., visual, haptic, audio) has an impact on the take-over time.

Importantly, the take-over time is not necessarily related to the quality of the take-over. This means that a short take-over time can still result in hazardous situations such as late response to conflicts (see e.g., Louw et al., 2017). Therefore, additional performance measures are needed as an indicator of the success of a take-over. The Take-Over Controllability rating is one such measure. It is a standardised video-based rating scheme that gives a global assessment of the criticality of take-over situations (Naujoks et al., 2018b). In a driving simulator study on behavioural changes with repeated usage of AD conducted in the L3Pilot project, all drivers managed to take back vehicle control when they had a time budget of 45 sec and when they had a time budget of 15 sec (Metz et al., 2021a). However, increased take-over times were found with increasing experience for drivers who had a large time budget of 45 sec available. Even though reaction times increased, no increase in objective criticality was found.

Several studies have also assessed the quality of the manual driving performance after automation deactivation in critical (TOR followed by conflict scenario) and uncritical scenarios, through a set of driving performance metrics. Examples of metrics used are maximum accelerations, maximum steering wheel angle, standard deviation of lane position, and crash rates (Mcdonald et al., 2019). Research suggests that drivers show a degraded manual driving performance (increased accelerations, late response to conflicts) when responding to a conflict scenario after automation, compared to a manual driving baseline (Gold et al., 2013, Louw, Merat and Jamson, 2015, Mcdonald et al., 2019). However, within the L3Pilot project, a study by Pipkorn et al. (2021) could not confirm this previously observed degraded driving performance after automation compared to a manual baseline. In their test-track study, drivers started steering at higher time-to-collision values (less critical) after automation compared to manual driving. One of the stated reasons behind the deviating findings was the timing of the TOR in relation to the presentation of the conflict scenario. While previous studies typically presented the TOR at the same time a conflict object appeared, the study by Pipkorn et al. (2021) presented the TOR prior to the conflict onset. It seems that when drivers receive a TOR some time before being presented with the conflict scenario, they have time to prepare for action (look at the road, put hands on the wheel, deactivate automation), and may therefore show a similar manual driving performance after automation compared to a manual baseline. This suggests that an important factor behind previously observed delayed response after automation compared to manual driving is the additional time needed for drivers to prepare to act (look towards the forward road, put hands on the wheel, deactivate automation).

For safety reasons, most take-over studies have been conducted in virtual environments. Driving simulators allow for controlled experiments to address specific research questions and hypotheses. For example, the impact of a specific driver state (e.g., sleep) on drivers' response to TORs can be investigated (Wörle, Metz and Baumann, 2021). Little research has currently been done in realistic environments (test track) and in real traffic. One of the reasons behind the current lack of these types of studies is the need for a real vehicle with a functioning and reliable ADF. Recently, so-called Wizard of Oz vehicles have enabled experiments to be performed in realistic and real environments (Naujoks et al., 2019, Pipkorn, Dozza and Tivesten, 2022, Pipkorn et al., 2021). However, to be able to consider the variety of situational factors (e.g., changing traffic) that can affect the success of a safe take-over, take-over studies need to be conducted on real roads, and in real traffic environments, to validate previous findings in driving simulators.

4.2.2 Behavioural adaptation and automation misuse

Depending on the level of automation, the driver might not need to physically control the vehicle but only remain vigilant (SAE L2) or might even be permitted to disengage from supervising the driving environment and engage in NDRTs (SAE L3+). The driver's behaviour during the drive, however, might not only change in ways that are foreseen by the designers of the system, but also in ways that are not intended. These changes in behaviour are referred to as "behavioural adaptation" (OECD, 1990).

One driving simulator study on changes in driver behaviour and attitudes when exposed repeatedly to a (simulated) ADF found that with increasing experience, drivers trusted the system more, directed less attention to the road, and engaged more in NDRTs (Metz et al., 2021a). These changes in behaviour might not have been anticipated by the designers of the system, but they are within the scope of legal use.

Other kinds of behavioural changes are more concerning: In the same study, drivers were also found to misuse the system by sleeping while the system was active, even though they were instructed to remain attentive to TORs. Half of the sample stated that they were also willing to sleep during the drive if they had a conditionally ADF available in reality (Metz et al., 2021b). Similar results were found for ordinary (non-professional) drivers who experienced an automated motorway driving system on real roads (Weber et al., 2021). Sleeping behind the wheel of a conditionally automated car is a clear misuse of automation.

Serter et al. (2017) suggest that, depending on the level of automation, various forms of automation misuse may increase. Some users might consider using AD when being drunk or watching videos, while they are required to monitor the automation. Automation misuse has to be defined according to the level of automation. Not only drivers but also other road users could be inclined to misuse automated vehicles, for instance by crossing the road closely in front of an AV (Millard-Ball, 2018). Misuse of automation is linked to high levels of trust or over-trust in the automation (Parasuraman and Riley, 1997). Trust has been shown to increase with increasing experience with an ADF (Dikmen and Burns, 2017, Metz et al., 2021a). The link between drivers' and other road users' behavioural adaptation to AD and automation misuse has to be understood in more detail. This is especially important to avoid automation misuse that can cause traffic hazards.

4.2.3 Mental models of AD

The driver's mental model of ADAS and AD affects how they use and evaluate a system. The mental model is defined as the "reflection of an operator's knowledge of a system's purpose, its form and function, and its observed and future system states" (Gaspar et al., 2020; p. 1). A high proportion of users of ADAS were found to have an incorrect mental model of the systems in their cars. In a survey on users of ACC, knowledge questions on the basic functions and basic purposes of the system were answered correctly by only about half of the user sample (Mcdonald, Carney and Mcgehee, 2018). For example, only 58% of users knew that if the vehicle ahead moves out of the detection zone, the ACC will accelerate. Drivers with an accurate mental model responded faster in critical situations (Gaspar et al., 2020). In a series of test-track studies with a partially ADF, 28% of participants crashed into a conflict object even though eye-tracking analysis showed that they had their eyes on the object. When questioned afterwards about why they did not respond, 13% stated that they did not realise the need to intervene. Some drivers were unsure or assumed that the vehicle was able to handle the situation, which reflects an automation expectation mismatch (Victor et al., 2018) and the wrong mental model of AD capabilities.

The more complex an automated system is, the more difficult it is for the user to obtain the correct mental model of system functionality. The risk of a cognitive mismatch between the user's mental model and the actual system output increases with such complexity (Baxter, Besnard and Riley, 2007). When the user detects a mismatch between their mental model and the system behaviour, they might correct the mismatch and get a more accurate mental model. If a mismatch remains undetected, the potential for critical situations due to missing or wrong actions by the user increases. Mental models of automation might be affected by biases (Seppelt and Victor, 2020).

Many researchers have studied drivers' mental model of ADAS (Beggiato and Krems, 2013, Forster et al., 2019, Gaspar et al., 2020, McdonaldCarney and Mcgehee, 2018) and found that the mode of learning how to use the system (Forster et al., 2019) and the level of information drivers receive about the system's behaviour (Beggiato and Krems, 2013) affect the development of the mental model. Drivers' expectations of the system's capabilities also depend on how the system is advertised and on its brand name. For example, systems with the word "Cruise" in their name were associated with lower levels of automation, while systems with the word "Assist" were associated with higher levels of automation (Abraham et al., 2017). Drivers may have a general mental model of an automated system that is based on the owner's manual or an introduction by the car dealer, and they gain a more applied mental model, including more detailed knowledge of specific operational conditions, once they experience concrete situations (Seppelt and Victor, 2020).

Seppelt and Victor (2020) provide an overview of applicable measures for mental models. They suggest the use of questionnaires for purpose, process, and performance, as well as for behavioural measures like monitoring behaviour, secondary task use, or response time to hazards, among others.

To date, research has focused on the driver's general mental model during use of lower levels of automation or driver assistance systems. Less research has been done on the applied mental model that develops with increasing experience of different driving scenarios and higher levels of automation. It can be hypothesised that the more situations are encountered by drivers, the more calibrated the mental model becomes. Knowledge about the development of a mental model of AD can be used to develop driver training programs for driving with AD that not only teach the correct handling of the function, e.g., its activation and deactivation, but also help to develop a correct mental model.

4.2.4 The "Out of the Loop" concept and Situation Awareness in Automated Driving

The automation of ever more parts of the driving task may be accompanied by a shift of the driver's attention from the road and driving-related cues to other tasks. Depending on the level of automation, this can be part of the system design or a misuse of the function.

The driver being distracted, inattentive, and thus "out of the loop" in L2 systems should be avoided for safety reasons; however, being "on the loop" and monitoring the system without being in physical control is possible (Merat et al., 2019). L2 systems currently on the market oblige the driver to keep their hands on the wheel and eyes on the road, thus remaining at least "on the loop".

In L3 and L4 systems, the system design is based on the driver engaging in NDRTs and thus being "out of the loop". However, at a system's functional limit, or during system errors, a TOR is issued to the driver. The driver is then required to get back into the loop and gain situation awareness to be able to take back vehicle control and responsibility.

Being "in", "on", or "out of" the control loop are not discrete states but rather levels on a continuum. Studies show that the more drivers are out of the loop of driving control during AD, the longer it takes them to resume vehicle control in critical situations (Gold et al., 2013, Louw et al., 2017). Characteristics of NDRTs can influence how "far" the driver is out of the loop. Drivers engaged with a manual-visual task have been shown to need more time to resume control after a TOR than drivers engaged with a visual task (Naujoks et al., 2019).

Situation awareness was first investigated in aviation and is closely linked to the out-of-the-loop concept. Situation awareness is defined as *"the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future"* (Endsley, 1988; p. 97). Situation awareness involves perceiving relevant cues in the environment (level 1), understanding their meaning in relation to the person's goals (level 2), and understanding what will happen in the future (level 3). Endsley (2018) identifies three mechanisms by which situation awareness is reduced due to driving automation:

- "(1) Poor vigilance when people become monitors, often coupled with increased trust or over-reliance on the automation,
- (2) Limited information on the behaviour of the automation and/or the relevant system and environment information due to either intentional or unintentional design decisions, and
- (3) A reduced level of cognitive engagement that comes from becoming a passive processor rather than an active processor of information."

The SAGAT (Situation Awareness Global Assessment Technique; Endsley, 1995), the SPAM (Situation-Present Assessment Method; Durso et al., 1998) and the SART (Situation Awareness Rating Technique; Taylor, 2017) are commonly applied measures in situation awareness research. In studies on AD, situation awareness is mainly investigated by means of eye-tracking measures, i.e. visual attention (Liang et al., 2021) or by response to critical events (Gold et al., 2013, Merat and Jamson, 2009). Also, the comprehension of a situation can be investigated by presenting situational cues in the traffic environment (MuellerReagan and Cicchino, 2021). Situation awareness is improved for drivers using ACC when they are motivated to detect objects in the environment (De Winter et al., 2014) and when warned with a two-stage instead of a one-stage warning in take-over scenarios (Ma et al., 2021).

For driving systems that do not require the driver to remain in or on the loop of driving control, but do require them to get back and gain situation awareness within a short time frame at system limits, the challenge remains: How can an out-of-the-loop driver gain situation awareness and how can they be supported by the system? To investigate the building of situation awareness in take-over scenarios, indicators for situation awareness should be chosen in a way that they reflect all three levels of situation awareness. This might include a mix of methods like the SAGAT, self-report measures, eye-tracking measures, or measures of driving performance and different study approaches like driving simulators and studies in real traffic. Depending on the approach, an assessment of situation awareness can differ.

4.2.5 Driver monitoring

One of the main human factors challenges of intermediate levels of automation is ensuring that the driver/user is capable of performing the role commensurate with the level of automation. At Levels 2 and 3 (and in some cases Level 4, for example, at the end of an ODD), this relates to ensuring that the driver is able to re-enter the physical and cognitive control loops to safely resume manual control of the driving task, while at Level 2 automation, this may also include ensuring the driver is effectively supervising the driving task (Louw, Merat and Jamson, 2015, Merat et al., 2019).

A key solution to ensuring such safe driver-automation interactions involves the use of driver state monitoring systems, which measure driver behaviour, attention, and readiness. Indeed, driver state monitoring is being included as part of the European New Car Assessment Programme (Euro NCAP) Safety Assist protocols from 2023 (Euroncap, 2021). The ADF may use information from the driver monitoring system to effectively manage communication between the driver and the ADF via an HMI, utilising real-time visual, auditory, haptic, and multimodal feedback. If the driver monitoring system detects that the driver is unfit to drive, the ADF may use this as a basis for deciding whether to bring the vehicle to a safe stop, using a minimum risk manoeuvre.

Driver state monitoring systems typically combine various sources of information, including information from cameras, steering wheel-based sensors, and wearable devices. There are a plethora of devices and indicators to assess the range of driver states (e.g., workload, fatigue, attention, emotion, and distraction — including visual, cognitive, and physical). These can be divided into physiological (e.g., measures reflecting the activity of the autonomic nervous system) and behavioural (e.g., movement of body parts, driving performance) indicators. While not typically used in driver state monitoring systems, subjective (e.g., self-report measures of sleepiness) indicators are commonly used in research settings as ground truth to validate objective indicators.

Physiological indicators typically include measurements of heart rate and heart rate variability; electro-oculogram, electroencephalogram, electrocardiogram, or magnetoencephalograph assessment; and evaluation of electrodermal activity, head movements, eye movement or pupil dilation, and blood pressure. Behavioural indicators may include posture (including hand, arm, head, trunk, and body position), facial expression, voice characteristics, reaction time, and lateral and longitudinal vehicle control. Subjective indicators include self-reported measures of perceived effort [e.g., Rating Scale for Mental Effort (RSME), Zijlstra and Van Doorn (1985), NASA Task Load Index (TLX), Hart and Taveland (1988)], fatigue, sleepiness (e.g., Karolinska Sleepiness Scale (KSS) Åkerstedt and Gillberg (1990)] and emotional state.

The current literature on driver monitoring focuses on the concept of readiness, an abstract concept used to define whether or not the system should intervene in the driver's monitoring task and provide assistance through the HMI. Georg et al. (2017) have defined readiness as "(…) *the fastest ability of the driver to get engaged in the driving task from the Non-Driving Related Task (NDRT) (…)*". Thus, a ready driver would be one capable of responding on time to a given scenario (see ISO/TR 21959-1:2020) where an intervention is required (Mioch, Kroon and Neerincx, 2017). Based on this construct, several studies attempt to correlate drivers' ability to avoid a critical take-over situation, or their self-reported readiness state, with a combination of physiological, behavioural, and subjective indicators, in order to create algorithms for real-time driver state estimation. For instance, Kim et al. (2018) were able to correlate drivers' reported readiness with physiological indicators such as heart rate variability and electrodermal activity. Similarly, Mariajoseph et al. (2020) were able to correlate drivers' probability of crash avoidance in a takeover, using the same metrics. Both studies report a real-time driver state monitoring algorithm, generated using the identified correlation to estimate whether the automation should support the driver in their monitoring task. When it comes to behavioural indicators, Baek et al. (2018) were able to predict drivers' reported drowsiness state based on an RGB camera, capturing their head position, posture, and facial expression (eyelid closure, and pupil dilation); and Zhou, Yang and De Winter (2021) created a machine learning algorithm able to correlate drivers' reported situation awareness levels to their eye movement patterns, extracted from an eye-tracking device. However, more research is needed to validate the accuracy of existing and novel methods of identifying driver states, while knowledge on the best/most successful HMI to be used for these systems is also lacking.

4.2.6 Teleoperation[1]

The automation of driving tasks is proceeding rapidly and is projected to bring about tremendous improvements also for public transport in terms of flexibility, safety, and efficiency (Litman, 2022). However, until fully AD according to SAE Level 5 (SAE, 2021) is feasible, driverless vehicles hardly appear to be a viable solution for public transport, since handling a large number of travellers imposes particularly high requirements on safety and reliability. In order to be able to use the benefits of AD while ensuring the fulfilment of legal and economic requirements, the teleoperation of AVs is a promising approach to bridge the gap between current technological shortcomings and the effective use of innovative solutions available today (Georg et al., 2018, Neumeier et al., 2019).

Embedded in the set of tasks and workflow of a public transport control centre, monitoring and operating will require much fewer human resources since one remote operator will be able to oversee the operation of multiple vehicles. Unlike in the current operation of AVs, the on-board presence of an operator in terms of a so-called security driver will be obsolete. Instead, a human driver, i.e., a remote operator who is not physically present on board the vehicle, re-enters the control loop as a fall-back solution. Mobile networks assure the exchange of information between the AV and the remote operator (Tang et al., 2014). In case of a system failure, the AV stops in a safe position and is connected to a remote operation centre, where the failure is inspected by a remote operator who takes over control of the AV, if necessary (Georg et al., 2018).

Although teleoperated vehicles are used in a wide range of applications, according to Winfield (2000), there are three characteristic elements that are part of each teleoperated application, namely operator interface, communication link and robot, in this case the AV. The operator interface usually consists of at least one display to visualise the videos from the

[1] The following paragraphs are adapted from Kettwich, C., & Schrank, A. (2021). Teleoperation of Highly Automated Vehicles in Public Transport: State of the Art and Requirements for Future Remote-Operation Workstations. In *27th ITS World Congress,* Hamburg, Germany, 11-15 October 2021.

AV's on-board cameras and additional status or sensor information. Furthermore, the operator interface requires input devices to enable the operator to enter commands or exert manual control of the AV. In road vehicles, this input device commonly consists of a steering wheel and pedals but could also be a joystick or a touch device. As the idea of teleoperating objects originates from the realm of robotics and aeronautics, the first HMIs for teleoperation served to remote-control robots as well as instruments and vehicles in space. The interaction between the operator and AV follows one of two ways: Either the operator interacts with the AV by entering input into the interface which is subsequently translated into driving actions by actuators, or conversely the sensors of the AV transmit data such as camera images to the interface, which in turn presents these data to the operator (Trouvain, 2006).

This basic design of a teleoperation HMI has been refined and extended by technological innovations like the creation of 360° images from multiple cameras (Bodell and Gulliksson, 2016), using head-mounted displays to present the images and sometimes additional information to the operator (Bout et al., 2017). Kettwich and Schrank (2021) designed and evaluated an HMI for a remote operator's workplace following the user-centred design process. This work is informed by extensive research on the work environment of remote operators, and by typical use cases and scenarios in remote operation (Kettwich et al., 2022).

For AVs, the communication link to the operator needs to be wireless. The connection must be designed to transfer the necessary data between the AV and the operator and vice versa with the least delay possible. Because of decoupling of the human perceptual process from the natural environment, human perception is often restricted in teleoperating environments (Tittle, Roesler and Woods, 2002). Thus, simple tasks may be more challenging due to a shortage of motion feedback and a restricted field of view; for example, spatial orientation and object identification tend to be weakened in a remote environment (Darken, Kempster and Peterson, 2001).

Latency, which refers to the delay between input action and output response, is one of the major difficulties of remote control, because the available transmission technologies are significantly limited. Latencies are very application-specific and of varying importance, depending on the speed and precision of the vehicle as well as the area in which it is operated (Bodell and Gulliksson, 2016). Latency in controlling a vehicle is caused by transmission delays in the communication channel, the steering method, or the sampling rate (Kay, 1995, Mackenzie and Ware, 1993). Studies on human performance show that humans are generally able to detect latencies between 10 and 20 msec (Ellis et al., 2004). Latencies in haptic and visual feedback below 100 to 200 msec do not reduce task performance, whereas higher latencies will decrease task performance depending on the task type and level of difficulty. According to Diermeyer et al. (2011), 400 to 500 msec is the highest tolerable latency, while impairment of task performance already occurs with a latency of approximately 200-225 msec (Mackenzie and Ware, 1993, Pongrac, 2011). Minimising latencies in information transmission even outweighs the importance of high-resolution graphic output (Pausch, 1991) or high frame rates (Bodell and Gulliksson, 2016).

Different control approaches are used in teleoperation. Fong and Thorpe (2001) distinguish between direct, multimodal/multisensor, supervisory control, and novel interfaces for vehicle teleoperation. Here, the latter three categories will be subsumed under the category "indirect control", since in modern interface designs their characteristics overlap significantly. The *direct control* approach uses hardware that mimics a vehicle's actual instruments, such as a steering wheel and pedals for accelerating and braking. The remote operator uses these instruments while being presented video imagery from cameras, data from on-board sensors, and sounds recorded by microphones attached to the vehicle. Even though this approach creates an environment very similar to sitting in the driver's seat on board the vehicle and therefore seems to be intuitive, the latency in data transmission does not provide the level of telepresence needed to safely steer the vehicle (Kay, 1995).

In contrast to direct control where the operator controls the AV directly and without the help of automation, in *indirect control*, the inputs and feedbacks take place at a higher level. One example of indirect control is the shared control approach where intermediate targets are defined by the supervisor. In case of remote-controlled shuttles, waypoints are set by the remote operator (Kay, 1995). A prerequisite of this approach is a certain degree of intelligence or autonomy of the shuttles to translate the control specifications using a local controller. Shared control requires human intervention only occasionally. Computational power and intelligence are used to translate human decisions into driving actions (Gnatzig, Schuller and Lienkamp, 2012, Kim and Ryu, 2013, Chen and Lu, 2015). Gnatzig, Schuller, and Lienkamp (2012) showed that trajectory-based driving is at least fast enough for inner-city traffic, the condition where it is likely to be used most frequently.

4.3 Overview of research questions

The overall topic of use of AD covers a range of different aspects on how drivers use and interact with such a system and of how such a system might impact the driver. Furthermore, within Hi-Drive, the focus is widened to other types of future users, including questions about the interactions of teleoperators with AVs. As a consequence, the research area of AD usage is one with many research questions that relate to a variety of diverse subtopics (see Table 4.1).

Table 4.1: Overview of research questions for the research area dealing with the usage of AD.

High-level research question	Medium-level research question
How can the transition of control at the boundaries of the ODD be improved?	How do drivers respond if they are required to take back control?
	Is manual driving after AD different?
	How can drivers be supported in resuming control?
What is drivers' usage of AD?	How does system usage change with repeated use?
	What affects drivers' visual attention during AD?
	What are the links between drivers' behaviour during AD use and their attitudes towards these systems?
What is drivers' understanding of AD while driving with AD?	What is drivers' mode awareness while driving with AD?
	What is drivers' mental model of AD?
What is drivers' situation awareness while driving with AD?	Which factors influence drivers' situation awareness while driving with AD?
	How does the driver gain situation awareness in takeover situations?
	What is the impact of drivers' situation awareness on takeover reactions?
Which NDRTs do drivers engage in while driving with AD?	Which factors influence NDRT engagement while driving with AD?
	What is the impact of cognitive distraction?
How can driver monitoring improve the handling of AD?	How can drivers' state be assessed?
	How can information on drivers' state be used to make AD usage safer?
	Which factors impact drivers' state?
How can AD be supported by teleoperation?	What is the task of an operator in teleoperation?
	How can HMIs that are adaptive to the state of the operator improve teleoperator performance?

5 User Evaluation – Interaction between AD and other traffic participants

5.1 Scope of this research area

According to Markkula et al. (2020), an interaction can be defined as "a situation where the behaviour of at least two road users can be interpreted as being influenced by the possibility that they are both intending to occupy the same region of space at the same time in the near future" (Markkula et al., 2020, p.10). In this research area, it is studied how AD needs to be designed to allow a smooth and safe interaction with other surrounding traffic participants. The focus of this research is on complex traffic environments where interaction with multiple road users and/or VRUs occurs.

5.2 State of the art

5.2.1 Interaction in urban traffic

Urban traffic can be considered as a social system in which vehicles, cyclists, and pedestrians interact and communicate with each other (cf. Rasouli and Tsotsos, 2019). To interact in this complex environment in a safe and efficient manner, communication is required to build up a common understanding between the actors interacting with each other (Färber, 2016). Focusing on the context of urban traffic, the communication between vehicles and other traffic participants, i.e., pedestrians or cyclists, can take place in different ways (Röhner and Schütz, 2016). These include:

- *Implicit, informal communication* which is not directly directed to the recipient, and the content of the message is not obvious at first glance, e.g., gestures, eye contact and vehicle movements (e.g., braking, cf. Ackermann et al., 2019, Bengler et al., 2020, Hagenzieker et al., 2020).
- *Explicit communication* involves a road user behaviour that does not affect his or her own movement or perception but can be interpreted as a signal or request to another road user (cf. Markkula et al., 2020).

Today's interaction between human drivers and pedestrians can be described as an interplay between implicit and explicit communication (cf. Dey and Terken, 2017). Implicit communication given by the vehicle, braking or speeding, is seen as an important indicator for pedestrians' crossing decisions, and is often used unconsciously (cf. Ackermann et al., 2019). Explicit communication is mostly needed in low-speed and low-distance traffic scenarios, when problems occur, e.g., when the vehicle does not show an expected behaviour (Dey and Terken, 2017, Färber, 2016, Lee et al., 2021, Uttley et al., 2020). Currently, the challenge is to determine the optimal interplay between implicit and explicit communication methods, to enable the safe and efficient interaction between actors in a mixed traffic environment involving AVs. This is particularly important for the interaction with other vulnerable traffic participants (such as pedestrians and cyclists, collectively called Vulnerable Road Users or VRUs), as they are at higher risk of getting injured in a collision (Dey and Terken, 2017, Lee et al., 2021, Schieben et al., 2019).

5.2.2 Other traffic participants' interactions with AVs

The introduction of AD will lead to a fundamental change in the interaction with traffic participants in urban traffic (Kauffmann et al., 2018). AVs will be introduced into *mixed traffic environments*, where they will coexist with others, including pedestrians, cyclists, and other VRUs. For driverless AVs, implicit, informal forms of communication will become obsolete, due to the absence of a human operator (Hagenzieker et al., 2020, Merat et al., 2018b, Merat et al., 2018a).

Today's *dyad of* interaction consisting of the human driver and other traffic participants will shift to a *triad of interactions* consisting of on-board users, vehicle automation, and other traffic participants (Schieben et al., 2019). In higher automation levels (SAE Levels 4 and 5), the on-board user will be more or less decoupled from the driving task (SAE, 2021). This shift of control can lead to new challenges for the interaction between AVs and other traffic participants, in terms of interaction and communication. This may induce additional risks, such as when VRUs become hesitant or over-reliant in their interactions with an AV, due to a lack of clarity on whether the vehicle they encounter is automated or manually driven (Hagenzieker et al., 2020).

It is also likely that AVs may be tested or blocked intentionally or unintentionally by VRUs, e.g., to see how they react in near collision situations, or because it is expected that these vehicles will always stop (Ackermann et al., 2019, Hagenzieker et al., 2020, Madigan et al., 2019, Merat et al., 2018b, Nordhoff et al., 2020c). Nordhoff et al. (2020c) revealed that respondents would be more cautious in crossing the road in front of an automated shuttle, due to a lack of trust in the behaviour of the automated shuttle and lack of eye contact with human drivers. These situations can be avoided if AVs and VRUs effectively interact with each other, communicating their intentions to one another, and agreeing on future motion trajectories (Merat et al., 2018a, Merat et al., 2018b).

Previous responsibilities that have been carried out by human drivers need to be replaced by vehicle automation to guarantee effective interactions in urban traffic. It has been suggested that a communication framework between all actors interacting with AVs can compensate for the absence of a physical driver (De Clercq et al., 2019, Merat et al., 2018a). In particular, VRUs depend on implicit and explicit communication to solve misunderstandings and prevent accidents (Habibovic et al., 2018, Schieben et al., 2019). Therefore, AD must be enabled to explicitly and implicitly inform other road users, e.g., about the vehicle's automation status, manoeuvre intention, and perception of the environment (Habibovic et al., 2018, Rettenmaier, Albers and Bengler, 2020).

5.2.3 Communication Tools for AVs

A range of tools and methods have been suggested to enable AVs to communicate implicitly and explicitly with other traffic participants, thereby informing them about the vehicle's intentions (Bengler et al., 2020). For example, dynamic human-machine interfaces (dHMIs) can transmit implicit information via vehicle dynamics, e.g., braking behaviour (Bengler et al., 2020). Secondly, external human-machine interfaces (eHMIs), as communication tools positioned on the outside of the AV, seem to be a promising approach for transmitting explicit information to other traffic participants. Example uses include information about the vehicle's current or future behaviour (i.e., driving mode and intention), cooperation manoeuvres, and perception of the environment (Dey et al., 2020, Habibovic et al., 2018, Schieben et al., 2019). However, there is still a paucity of knowledge on the usefulness of eHMIs, given that this research area is in its infancy and most of the research has been done for a single person interacting with a single vehicle.

It is also important to note that the most effective eHMIs are those which communicate their intentions to all traffic participants (i.e., not only pedestrians) (Tabone et al., 2021). Bazilinskyy, Dodou, and De Winter (2019) have provided an overview of the large number of eHMIs proposed by industry and available in the scientific literature, which provides regulatory challenges, if there is a requirement to harmonise the external communication of AVs across OEMs, and in different countries. The design of eHMIs can be harmonised in terms of colours, form, message, and location. However, it is still an open question as to whether eHMIs should be detached from the vehicle, in the form of augmented reality messages (Tabone et al., 2021).

So far, there are promising results concerning the effect of eHMIs on other traffic participants' perceived safety and acceptance (De Clercq et al., 2019, Kitazaki and Daimon, 2018), comfort, trust (Holländer, Wintersberger and Butz, 2019), and pedestrians' willingness to cross (Dey et al., 2020). Additionally, the use of an eHMI can positively affect pedestrians' crossing behaviours, i.e., assisting with earlier crossing decisions and creating higher certainty about their decision (Wilbrink et al., 2021). However, the visibility and familiarity of the eHMI are also important factors affecting traffic participants' comprehension of, and reaction to, these eHMIs, with more familiar and more easily visible forms of communication leading to faster crossing decisions (Lee et al., 2021). This issue of familiarity is especially important, as the same eHMIs have been found to convey different messages, with the same message also assumed by different eHMIs (Lee et al., 2019).

Research has also shown that eHMIs are especially useful at low speeds, with pedestrians having time to interpret and react to the information displayed, while a correct interpretation and corresponding action is more difficult at further distances and higher speeds. Furthermore, very small differences in the ratings of fundamentally different eHMIs have been found in terms of acceptance and their effects on behaviour (Tabone et al., 2021). Focusing on the design of eHMIs for different vehicle types, current research also suggests that eHMIs have a positive effect on pedestrians' interactions with an automated bus, in terms of pedestrians' perceived safety and perceived information quality (Lau, Le and Oehl, 2021).

To enhance communication by AVs, it would be useful to combine eHMI communication and vehicle movement, i.e., by using dHMI, as pedestrians use implicit and explicit communication to interact in urban traffic (Dey and Terken, 2017, Kaleefathullah et al., 2020, Lee et al., 2021). In a study by Dey et al. (2021), different braking behaviours (dHMI) were combined with eHMI. The results indicated that pedestrians' decisions to cross were generally based on the vehicle's dynamics rather than on the eHMI message. For conditions in which the vehicle behaviour (dHMI) contradicted the eHMI, pedestrians relied on the vehicle's yielding behaviour (Dey et al., 2021). In contrast, LauLe and Oehl (2021) found that pedestrians' willingness to cross tended to rely on the eHMI when interacting with an automated bus, even if the eHMI presented signals inconsistent with the vehicle's behaviour. This addressed possible negative effects of eHMIs shown in other studies, such as over-trust in eHMIs (Holländer, Wintersberger and Butz, 2019, Kaleefathullah et al., 2020). Overall, future research should focus on defining the interplay of both communication tools (dHMI and eHMI) with the aim of creating a more holistic communication strategy of AVs with other traffic participants (Bengler et al., 2020, Dey et al., 2021). Furthermore, more complex traffic scenarios, including the interaction of AVs with more traffic participants, should be addressed in order to tackle more realistic interactions (Dey et al., 2020, Wilbrink, Nuttelmann and Oehl, 2021). Finally, augmented reality, which allows the user to perceive the real world with virtual objects (e.g., glasses) that are overlaid or embedded in it, could also facilitate the communication between AVs and external road users. (Tabone et al., 2021).

5.3 Overview of research questions

With the focus on the interaction of AD and its surrounding traffic participants, the following research questions are defined (see Table 5.1):

Table 5.1: Overview of research questions for interaction between AVs and other road users.

High-level research question	Medium-level research question
How can ADFs be designed to improve implicit communication with other traffic participants?	In which situations are vehicle movement patterns (dHMI) sufficient as implicit communication?
	What vehicle movement patterns (dHMI) can be manipulated and included in AD design to improve implicit communication?
What is the impact of externally presented HMIs (eHMI) as additional explicit communication?	In which situations do eHMIs (additional to implicit communication via dHMI) improve the communication between traffic participants?
	Do communication requirements for eHMIs vary between user groups?
	Are eHMI strategies scalable?
	How do traffic participants react to eHMIs?
	How do infrastructure and eHMI impact the behaviour of VRUs?
	What information does the surrounding driver need on eHMIs?
	How are eHMIs evaluated?

6 Effects Evaluation – Availability of AD

6.1 Scope of this research area

The first research area within the effects evaluation looks at the impact of the enablers on AD availability. Until now, one main challenge for AD has been to allow its continuation in various challenging situations (e.g., due to infrastructure or environmental conditions). Within Hi-Drive, new technical solutions (called enablers) are being developed and tested that will enable AVs to drive in previously unmanaged situations and that make AD performance more robust and reliable. In this research area it will be assessed, on the level of measurable AD availability, to what extent the enablers are able to extend the AD functionality to previously non-covered situations (i.e., ODD extension), to what extent new driving scenarios can now be handled by AD, and to what extent AD robustness can be improved by the technical solutions developed in Hi-Drive.

6.2 State of the art

At the current state of AD, only systems with very constrained ODDs have been made available to the public. One example is the SAE Level 3 System by Mercedes, which fulfils UN-R157 for a Level 3 system and is thus able to achieve automated driving during traffic jams (up to 60 km/h) without the driver having to intervene (Mercedes-Benz, 2021). In the US, three companies (Nuro, Waymo, and Cruise) hold a permit to deploy driverless vehicles (Dmv, n.d.). These operations are limited to certain geographic regions. For all operations with AVs, including those with human supervision, the Californian DMV requires companies to report the number of disengagements per miles driven (DMV, n.d.). The reported numbers highlight differences between the companies but do not allow to estimate the causes of disengagements from the numbers reported, thus the actual readiness of the individual ADF cannot be judged. Sinha et al. (2021) analysed the reasons stated for disengagements: Most relevant, at 56.1%, were system failures or driver-initiated disengagements (25.57 %); 9.98% were due to road infrastructure, 5.0% to the behaviour of other road users, 1.55% to construction zones, and 0.8% to weather. From the data it is not possible to judge the actual relevance of these reasons, as there is no information on what the testing approach was, thus e.g., bad weather conditions may be underrepresented.

The NHTSA (National Highway Traffic Safety Administration, U.S) has issued a standing general order on crash reporting for vehicles with Level 2 ADAS or with ADF (NHTSA, n.d.). Favarò et al. (2017) present an analysis of the reports from 2014 to 2017. Although the reported data contain more detail than the disengagement reports, it is not directly possible to derive which scenarios or ODD aspects pose the biggest challenges to the automated vehicle. Thus, such analyses would require additional internal information from manufacturers.

Feig et al. (2019) highlight the relevance of including challenging conditions in the ADF's ODD by analysing data from SHRP 2 (the 2nd Strategic Highway Research Program) (Campbell, 2012). Considering situations from crashes, near-crashes, and baseline situations, they provide a top-down analysis of what impact the exclusion of certain challenges within the ODD has on the overall availability of the system, as well as the potential avoidance of crashes or near crashes. From an ADF operating on interstates, bypasses, and highways with no traffic signals, they gradually exclude various ODD aspects and state what percentage of situations are still included. The aspects considered are:

- Traffic control
- Snowy/icy roads
- Exits/entrance
- Lane change/merging
- Construction zones
- Speed limits: 130, 100, 80, 60 km/h
- Traffic jams

Their analysis shows that excluding the most challenging ODD aspects (the first five bullets above) cuts the availability of the system down by 18.4%. Confining speed range of AD to traffic jams only would result in a reduction of availability to 3.9% of the analysed situations. For crashes, it becomes apparent that the most challenging ODD aspects have an even greater impact. The five aspects mentioned above reduce addressable crash and near-crashes to roughly 65% of what they would be otherwise. Confining speed range to traffic jams results in a 9% drop in addressable crashes. Comparing the SHRP 2 data with crash data from GIDAS (German In-Depth Accident Study) shows a less marked reduction (85% for the elements considered before and 9% for traffic jams).

Pfeil et al. (2022) introduce a taxonomy of corner cases for AD, many of which include ODD extension or defragmentation. They classify corner cases as resulting from a) Environment, b) Functional Constraints, or c) System-Internal boundaries (Table 6.1). Corner cases that fall under Environment or Functional Constraints have relevance for ODD extension. Within Hi-Drive, it will need to be considered that depending on how common they are, some of the listed corner cases will be pertinent for ODD extension evaluation, whereas those that are less frequent will relegated to the edge-case database under development.

Table 6.1: Classification of corner cases according to Pfeil et al. (2022)

Corner Case	Environment	Functional Constraints	System – Internal conditions
New object type	X		
Traffic routing	X		
Weather conditions	X	X	
Occlusion / Near crash	X	X	X
Speed range		X	
Road type		X	
Behaviour dynamic objects	X		X
Unspecified reaction		X	X
Faulty data processing			X
Perception			X
Runtime behaviour			X

Maddox, Sweatman, and Sayer (2015) define three technologies: "Connected", "Automated Vehicles", and "'Big Transportation Data", all of which they believe must be combined to achieve maximum positive societal impact. In support of this they present an overview of the advantages and disadvantages of the first two, as well as their relative benefits in achieving maximum impact.

Parekh et al. (2022) list the key AV technologies identified by a structured literature search and list the main technological challenges as follows:

- Environment perceptions
- Pedestrian detection
- Path planning
- Vehicle cyber security
- Motion control.

Similarly, Liu et al. (2020) define the current challenges as arising within environment sensing, mapping and localisation, V2X communications, sensor fusion, and planning, decision making, and vehicle control. The core challenges these technologies need to address are safety and handling of edge cases. Morales-Alvarez et al. (2020) review the literature on TORs within conditional automation and list the complexity factors that contribute to situations in which TORs typically appear, enabling each to be considered within the appropriate context.

Apart from objective complexity, subjective complexity is also considered, which among other things takes into account the urgency of the situation.

Table 6.2: Objective complexity factors affecting take-over requests according to Morales-Alvarez et al. (2020)

Complexity Factor	Specific context	
Traffic Situation	Traffic density	High
		Low
Road conditions	Road geometry	Curved
		Straight
	Road lanes	
Control transfer	Haptic guidance	
	Abrupt transition	

Figure 6.1 illustrates how such currently existing gaps of AD availability occurring during one hypothetical trip with AD will be addressed by enablers developed in Hi-Drive.

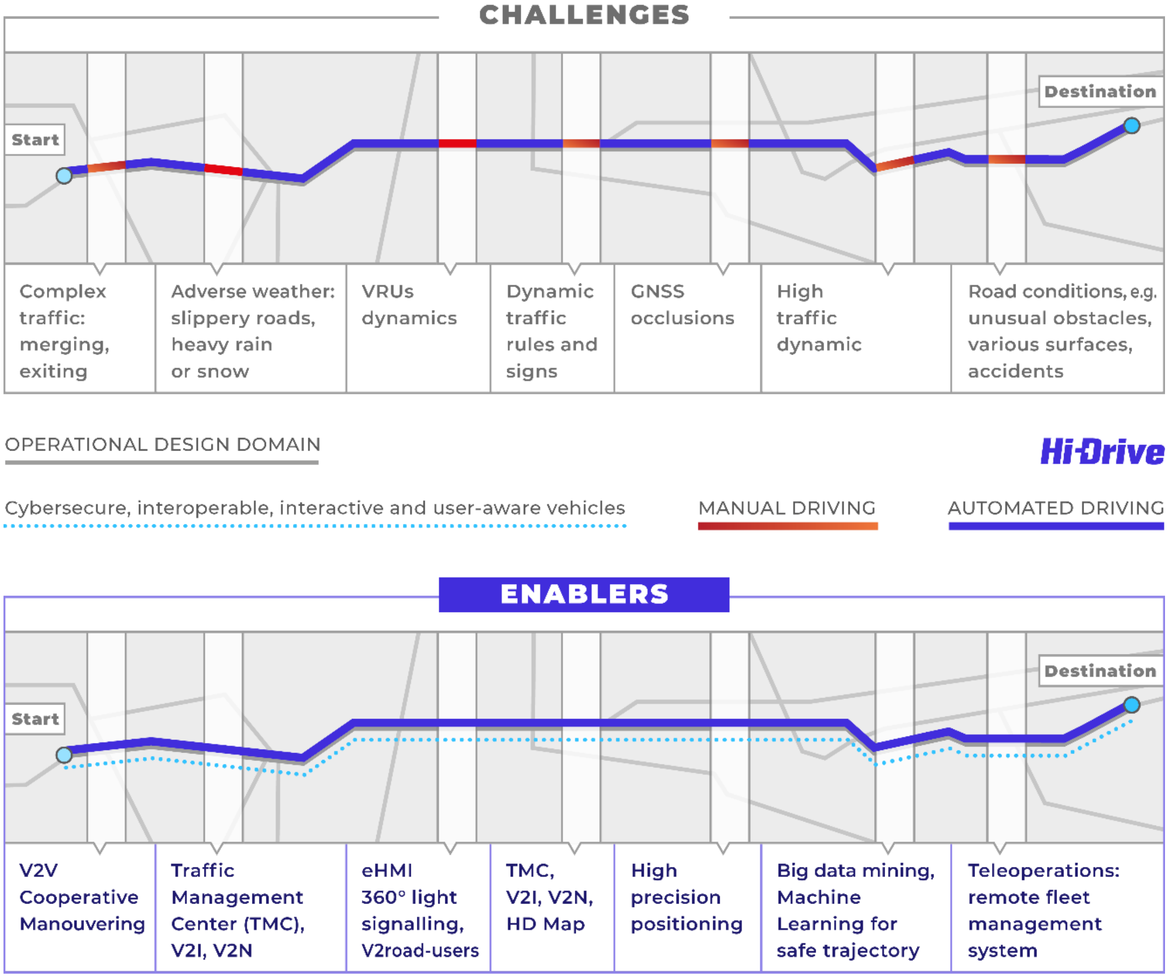

Figure 6.1: Illustration of impact of enablers on ODD defragmentation.

Within SP2, different technical solutions will be developed and implemented with which the gaps in AD availability can be addressed. These are clustered into four technology areas (see also D3.1, sec. 2.1.4):

- Vehicles Communication: These are enablers that are aimed at ODD defragmentation by using connectivity, either via direct communication or via cellular communication. This includes Vehicle to Vehicle Communication, Vehicle to Infrastructure and Infrastructure to Vehicle Communication, Vehicle to Cloud Communication (Edge and Core), and Vehicle Intention Communication.
- High precision positioning techniques: These enablers are aimed at enhancing AD robustness in situations with currently unstable positioning and at ODD extension by integrating new situations (e.g., tunnels) into the ODD. They include georeferenced cloud services, sensor fusion for localisation, and positioning relying on ranging signals.

- CAD Cybersecurity (shielding from V2X cyberattacks) will be ensured by Threat Analysis, Risk Assessment, and V2X Cyber-risk Mitigation.
- CAD Machine Learning (ML) Techniques will be used to improve AD in various areas: the CAD ML Toolkit for ML developers, CAD ML Perception, Object Detection and Classification, CAD ML Decision-Making, and CAD ML Driver Monitoring.

Within this research area, the focus is not on a detailed and specific evaluation of single enablers but on the enablers' impact on overall AD performance with regard to ODD definition and robustness of AD availability in challenging nominal (e.g. rain) or extended (e.g. motorway on-ramps) ODD conditions. Therefore, we will evaluate the extent to which the enablers help to increase AD availability under challenging conditions or include new situations into the ODD, and to what extent the enablers reduce the frequency of TORs due to ODD boundaries. In other words, the impact of enablers on AD availability will be evaluated, focusing on the use cases of the enablers. A complete list of use cases and test scenarios addressed in Hi-Drive, and the types of ODD extensions considered therein, is provided by Bolovinou et al. (2022).

6.3 Overview of research questions

Table 6.3 gives an overview of the research questions on AD availability. Enabler-specific analysis will be covered by SP2 and is not part of the AD-level research question list addressed by this deliverable. It is planned that the analysis will focus on driving behaviour in the Hi-Drive use cases like driving in adverse weather conditions, driving through construction sites, driving in tunnels, driving in roundabouts, etc. Where applicable, the following research questions will be addressed per use case. Therefore, Table 6.3 lists for each research question also use cases to which the research question might be applicable.

Table 6.3: List of research question in the research area on AD availability. Use cases that might be evaluated by the different research questions are listed as well. The final use case list for each research question will be defined in the Analysis plan for effects evaluation (D4.6). M = Motorway driving, U = Urban driving, R = Rural driving.

High-level research question	Medium-level research question	Use cases
To what extent do the enablers extend the AD functionality?	To which environmental conditions do the enablers extend the ODD?	M - Moderate or heavy raining R - Arctic uninterrupted driving in specific conditions U - Urban canyon driving
	To which road infrastructure elements do the enablers extend the ODD?	M - Cooperative lane merging/exiting M - Lane merging / exiting / interchange M - Special or temporary road infra crossing – Tunnel crossing; Road construction crossing U - Cooperative non-signalised intersection – Left turn; Roundabout crossing U - Cooperative signalised intersections U – Non-signalised intersections – Left turn, Right turn
	To which driving scenarios do the enablers extend the AD functionality?	M - Cooperative overtaking M - Lane changing U - Cooperative non-signalised intersection - Re-routing to avoid congestion/hazard in front
To what extent do enablers enhance AD robustness?	To what extent do enablers enhance AD robustness in challenging environmental conditions?	M - Moderate or heavy rain R - Arctic uninterrupted driving in specific conditions U - Urban canyon driving

High-level research question	Medium-level research question	Use cases
	To what extent do enablers enhance AD robustness in challenging road infrastructure conditions?	M - GNSS interruption; M - Approaching elevated bridge M - Various lane localisation problems M - Handling an event notification about an event in the range 0.5–2km ahead – dynamic road signage
	To what extent do enablers enhance AD robustness in challenging driving scenarios?	M - Lane changing U - Cooperative urban driving – Stop-n-go, Speed adaptation due to hazard in front U - Driving in lane M - Handling an event notification about an event in the range 0.5–2km ahead – hazard notifications

7 Effects Evaluation – Effect of AD on driving behaviour

7.1 Scope of this research area

The next research area covers questions that address the effect of AD and of enablers on driving behaviour of the AD and of other surrounding traffic participants based on vehicle data. It is analysed how driving changes with AD and its enablers compared either to manual driving or to a less complex AD version without integration of the newly developed enablers. It is planned for this research area to focus on analysing changes of driving behaviour in the use cases addressed by the enablers.

7.2 State of the art

Many research projects related to the evaluation of driving behaviour with AD have applied a scenario-based analysis (e.g., Rösener et al., 2018a, Rösener et al., 2016, Metz et al., 2013, Hargutt et al., 2014). A comprehensive list of scenarios for safety impact assessment has been derived by Rösener et al. (2018a); this catalogue was developed for safety-relevant scenarios and thus only includes scenarios from which safety-relevant interactions with other traffic participants may arise.

Based on the literature, a scenario-based approach for analysing the effects of AD on driving behaviour was applied in L3Pilot. Within that project, a large-scale evaluation of the impacts of AD on driving behaviour was carried out. The analysis was based on data from about 100 vehicles that have been operated on European roads, by different manufacturers and equipped with pre-series technology enabling AD. L3Pilot addressed three different driving domains: motorway, urban, and parking (Griffon et al., 2019).

Like in Hi-Drive, the overall methodology for L3Pilot was derived from the FESTA methodology FOT-Net Version 7 (2018) and applied to the special condition of a pilot study (Metz et al., 2020). As multiple manufacturers and suppliers operated AVs within the project, different vehicles were operated in different locations. The goal of the evaluation was not to benchmark between the different systems. Instead, a scenario-based evaluation approach was applied: In-line with the scenario-based approach all driving data was segmented into driving scenarios, for which performance indicators were then derived. The performance indicators were set up to answer the project research questions (Hibberd et al., 2018).

For each performance indicator and driving scenario, a non-parametric statistical test was carried out in L3Pilot to answer the research question of whether AD has an impact on the different performance indicators compared to manual driving. Given the large amount of data per performance indicator, most tests showed significant results. As described by

Rösener et al. (2018b), besides the statistical test the effect size was evaluated as well. Additionally, the change in percent was evaluated.

For the evaluation of driving scenarios which can in theory have an indefinite duration, chunking was applied. According to Dozza and Bärgman (2010), the duration of a scenario is a confounding factor for the evaluation of parameters concerning performance indicators like mean values or standard deviation of certain measures. With this process, long scenario instances are divided into multiple non-overlapping instances of fixed duration, which eliminates scenario duration as a confounding factor. In the case of L3Pilot, the chunked duration was set to 10 sec.

The main findings from the technical evaluation addressing AD performance within L3Pilot (Weber et al., 2021) include, for motorway ADF:

- While driving with the ADF, speed is significantly reduced across scenarios.
- While driving with the ADF, the distance kept to the lead vehicle is significantly increased.
- While driving with the ADF, lane keeping is significantly more stable.
- Driving with the ADF leads to a reduction of lane changes of the ADF vehicle and approaching scenarios. More driving time is spent in stable scenarios like car following.

For urban ADF, the key findings are the following:

- Tested systems are at a lower readiness level compared to motorway systems, so the results need to be considered carefully.
- Due to the complexity of the urban use case requiring a large amount of driving data to cover all facets of urban driving, a clear effect of urban ADFs cannot be stated in L3Pilot.
- Overall, ADFs tend to spend more time within intersections given their more cautious approach to conflicts.

The results from L3Pilot on the impact of AD on driving are in line with the results of Várhelyi et al. (2021). They conducted test drives on German motorways to assess user-related issues of Level 3 AD. In total, 21 persons drove twice along the test route, once with the system switched off and once with the system active. In general, AD affected driving positively (e.g., smoother accelerations, speed according to speed limit and traffic conditions, fewer dangerous lane changes, and correct distance to other vehicles). However, in that study conflicts and sudden braking events were observed more often on rides with the system active.

7.3 Overview of research questions

For Hi-Drive, the scenario-based analysis will focus on driving behaviour specifically in driving situations addressed by the enablers. This means that the analysis will go beyond the analysis of the most frequent driving scenarios (like following or free driving) already investigated in other projects (e.g., L3Pilot). Instead, it will focus on driving behaviour in the Hi-Drive use cases like driving in adverse weather conditions, driving through construction sites, driving in tunnels, driving in roundabouts, etc. Where applicable, the following research questions will be addressed per use case. Therefore, Table 7.1 lists for each research question also use cases to which the research question might be applicable.

Table 7.1: List of research questions on the effect of AD on driving performance. Use cases that might be evaluated for the different research questions are listed as well. The final use-case list for each research question will be defined in the analysis plan for effects evaluation (D4.6). M = Motorway driving, U = Urban driving, R = Rural driving.

High-level research question	Medium-level research question	Use cases
What is the effect of AD and its enablers on safe driving behaviour?	What is the effect of AD and its enablers on the frequency of incidents?	M - Cooperative lane merging / exiting / overtaking M - Lane merging / exiting / interchange M - Special or temporary road infra crossing – Tunnel crossing; Road construction crossing M - Handling an event notification about an event in the range 0.5–2km ahead U - Cooperative non-signalised intersection / Roundabout crossing U - Cooperative signalised intersections U - Driving in lane U - Overtaking U – Non-signalised intersection crossing U - Cooperative lane merging / exiting U - Speed adaptation due to hazard in front M - Moderate or heavy rain R - Arctic uninterrupted driving in specific conditions
	To what extent do enablers support timely re-routing to avoid an ODD exit?	M - Handling an event notification about an event in the range 0.5–2km ahead – hazard notifications; U - Speed adaptation due to hazard in front

High-level research question	Medium-level research question	Use cases
	To what extent do enablers support timely system-user control transition in the case of a TOR due to an upcoming ODD exit?	M - Handling an event notification about an event in the range 0.5–2km ahead – hazard notifications; U - Speed adaptation due to hazard in front
What is the effect of AD and its enablers on comfortable driving behaviour?	What is the effect of AD and its enablers on lateral acceleration?	M - Cooperative lane merging / exiting / overtaking M - Lane merging / exiting / interchange M - Special or temporary road infra crossing – Tunnel crossing; Road construction crossing M - Handling an event notification about an event in the range 0.5–2km ahead U - Cooperative non-signalised intersection / Roundabout crossing U - Cooperative signalised intersection crossing U - Non-signalised intersection crossing M - Lane changing U - Cooperative urban driving – Stop-n-go, Speed adaptation due to hazard in front U - Driving in lane U - Overtaking M - Moderate or heavy rain R - Arctic uninterrupted driving in specific conditions
	What is the effect of AD and its enablers on longitudinal acceleration?	M - Cooperative lane merging / exiting / overtaking M - Lane merging / exiting / interchange M - Special or temporary road infra crossing – Tunnel crossing; Road construction crossing

High-level research question	Medium-level research question	Use cases
		U - Cooperative non-signalised intersection – Roundabout crossing U - Cooperative signalised intersections U - Non-signalised intersections – Left turn; Right turn M - Handling an event notification about an event in the range 0.5–2km ahead – hazard notifications; dynamic road signage U - Speed adaptation due to hazard in front U - Overtaking U - Cooperative urban driving – Stop-n-go, Speed adaptation due to hazard in front U - Driving in lane M - Moderate or heavy rain R - Arctic uninterrupted driving in specific conditions
What is the effect of AD and its enablers on efficient driving behaviour?	What is the effect of AD and its enablers on longitudinal driving stability?	M - Cooperative lane merging / exiting / overtaking M - Lane merging / exiting / interchange M - Special or temporary road infra crossing – Tunnel crossing; Road construction crossing U - Cooperative non-signalised intersection – Left turn; Roundabout crossing U - Cooperative signalised intersections U - Non-signalised intersections M - Handling an event notification about an event in the range 0.5–2km ahead – hazard notifications; dynamic road signage

High-level research question	Medium-level research question	Use cases
		U - Speed adaptation due to hazard in front U - Overtaking U - Cooperative urban driving – Stop-n-go, Speed adaptation due to hazard in front U - Driving in lane M - Moderate or heavy rain R - Arctic uninterrupted driving in specific conditions
What is the effect of AD and its enablers on interacting with other road users?	What is the effect of AD and its enablers on the relative speed to surrounding road users?	M - Cooperative lane merging / exiting / overtaking M - Lane merging / exiting / interchange M - Handling an event notification about an event in the range 0.5–2km ahead U - Special or temporary road infra crossing – Road construction crossing U - Cooperative non-signalised intersection / Roundabout crossing U - Cooperative signalised intersection crossing U - Non-signalised intersections M - Moderate or heavy rain U - Driving in lane U - Overtaking
	What is the effect of AD and its enablers on the distance to surrounding road users?	M - Cooperative lane merging / exiting / overtaking M - Lane merging / exiting / interchange M - Handling an event notification about an event in the range 0.5-2km ahead

High-level research question	Medium-level research question	Use cases
		U - Special or temporary road infra crossing – Road construction crossing U - Cooperative non-signalised intersection / Roundabout crossing U - Cooperative signalised intersection crossing U -Non signalised intersections M - Moderate or heavy rain U - Driving in lane U - Overtaking
What is the effect of AD and its enablers on position in the lane?	What is the effect of AD and its enablers on variation of lane position?	M - Cooperative lane merging / exiting / overtaking M - Lane merging / exiting / interchange M - Handling an event notification about an event in the range 0.5–2km ahead M - Special or temporary road infra crossing – Tunnel crossing; Road construction crossing M - Moderate or heavy rain U - Driving in lane U - Overtaking R - Arctic uninterrupted driving in specific conditions
	What is the effect of AD and its enablers on the preferred lane position?	M - Cooperative lane merging / exiting / overtaking M - Lane merging / exiting / interchange M - Special or temporary road infra crossing – Tunnel crossing; Road construction crossing

High-level research question	Medium-level research question	Use cases
		M - Handling an event notification about an event in the range 0.5–2km ahead U - Cooperative non-signalised intersection / Roundabout crossing U - Cooperative signalised intersection crossing U - Urban driving – non signalised intersections U - Driving in lane U - Overtaking M - Moderate or heavy rain R - Arctic uninterrupted driving in specific conditions
What is the effect of AD and its enablers on the time to complete a test-driving scenario?		M - Cooperative lane merging / exiting / overtaking M - Lane merging / exiting / interchange M - Handling an event notification about an event in the range 0.5–2km ahead U - Cooperative urban driving – Stop-n-go, Speed adaptation due to hazard in front U - Cooperative non-signalised intersection / Roundabout crossing U - Cooperative signalised intersection

8 Effects Evaluation – Impact of AD after market introduction

8.1 Scope of this research area

It is expected that after market introduction, AD will not only impact driver comfort and vehicle behaviour during single drives but might also have a wider impact on the traffic system and society as a whole. The last research area deals with the large-scale impacts of AD and the enablers after market introduction.

8.2 State of the art

8.2.1 Safety impacts

The number of fatalities and injuries caused by road accidents involving AVs are the most important key performance indicators (KPIs) when evaluating the safety impacts of AD (e.g., Rämä and Kuisma, 2018). However, since automated passenger vehicles (SAE L3) are currently typically driven as part of field tests on public roads or on test tracks, the lack of AV-related crash data limits this type of analysis.

Due to the limited information on accident involvement of AD, the safety effects of AD have been identified through other approaches. The main findings of the most relevant studies are summarised below by method. All these studies indicate the safety benefit potential of AD. It is important to note that each study used its own definition of AD and considered different technical maturities of AD. Therefore, the assumptions used in each study should be reviewed carefully when interpreting the results. The variation in assumptions also makes the comparison of study findings challenging.

Analysis of accidents involving AVs on public roads (real-life crashes during testing of AVs)

All studies analysing accidents involving AD have exploited accident data from the database maintained by the California Department of Motor Vehicles, which includes accident reports filed by several car manufacturers testing AD on public roads in California, U.S. The analysis by Favarò et al. (2017) comprised an in-depth examination of 26 accident reports from 2014–2017. They found that the most frequent accident type was rear-end collisions (62% of cases), with manually driven vehicles driving into the AV's rear. In most situations, the AV was at zero or close-to-zero speed. In 22 of the 26 reported accidents (85%), the AV was not at fault. Wang and Li's (2019) analysis covered 113 accidents from 2014–2018 (86% of cases included only property damage, no injury); they discovered that crash severity significantly increases if the AD is responsible for the crash. They also determined that serious injuries were likely to happen on highways due to high driving speeds. Ye et al. (2021) studied 133 reports, including 24 injured individuals in 19 crashes involving AVs from 2017 to 2019. They found that 71% of the injured persons were AV occupants and that the head and neck were the most common injury sites.

Analysis of accident data

Kuehn and Bende (2019) analysed motorway accidents involving at least one passenger car from the database of the German Insurers Accident Research (n=246, 2007–2013). According to their analysis, it can be expected that cars driving in automated mode will still be involved in accidents. An active Level 3 function could prevent up to 6% more motorway accidents than modern cars equipped with driver assistance and comfort systems. However, the authors note that possible negative effects of L3 automation, which have not been quantified up to now, may decrease this potential significantly. Accidents caused by lane change will remain a big challenge for automated systems. An L4 system which drives in automated mode could prevent 21% more motorway accidents than modern cars equipped with driver assistance and comfort systems. It is important to note that the safety benefits reported here are additional benefits to those obtained by ADAS. It should also be noted that the definitions of AD in this study vary from those in the SAE J3016 standard and hence the results of this study should be interpreted with care.

Utriainen and Pöllänen (2020) and Utriainen (2020) assessed the potential impact of AD (Levels 4 & 5) on pedestrian safety in Finland by estimating which accidents could be avoided if manually driven cars had been replaced by AVs. Both analyses exploited the same dataset, i.e., in-depth investigations of fatal crashes involving pedestrians from 2014 to 2016 in Finland (n = 40). Utriainen and Pöllänen (2020) estimated that 37 of 40 crashes would likely have been avoided by highly AVs if pedestrian safety were to be prioritised (i.e., AVs would always take necessary safety precautions when pedestrians are identified nearby or in the proximity of the planned driving path). Utriainen (2020) focused on different scenarios in terms of AV capabilities and the possibilities for the driver to bypass the system and take control of the vehicle. The results show that in a basic scenario where the AV is not able to operate in adverse conditions and without visible lane markings, 8–11 (20–28%) of 40 fatal pedestrian crashes could have been avoided by highly AVs. The corresponding numbers for the other scenarios were: 19–24 (48–60%) for advanced scenario (AV capable of operating in low-light conditions and without lane markings, but not in adverse weather conditions) and 22–29 (55–73%) for full automation scenario (AV capable of operating in various weather and traffic conditions).

Combs et al. (2019) analysed the data from the Fatality Analysis Reporting System (FARS) from all the U.S. states and the District of Columbia (n=3,386 preventable pedestrian fatalities in 2015) to investigate the potential of AVs for reducing pedestrian fatalities based on functional ranges of the following pedestrian sensor technologies: visible-light cameras (VLC), light detection and ranging (LiDAR), and radar. The results show that the detection technologies vary widely in their potential to detect pedestrians and avoid fatal collisions with pedestrians, from less than 30% (VLC in freeway conditions) to over 90% (VLC+LiDAR+radar) of preventable fatalities.

Multi-agent traffic simulation

Kitajima et al. (2019) simulated traffic on a prescribed area in the city of Tsukuba in Japan. Five scenarios of increasing levels of penetration of AVs (starting with manual driving and continuing to different combinations of automated emergency braking, lane departure warning, and SAE Level 4 AD) were implemented to estimate their impact on safety. Under manual driving, the system simulated 859 crashes, which tended to occur in locations similar to real-world accidents. In the scenario with the highest automation level (75% Level 4 AD and 25% Automated Emergency Braking + Lane Departure Warning), the number of predicted crashes decreased to 156 cases. Overall, the higher the automation level, the lower the crash rate.

Simulation-based surrogate safety measures approach

Morando et al. (2018) explored the safety impacts of AD (L4, fully automated) through the number of conflicts extracted from simulations by using two case studies: a signalised intersection and a roundabout with various AD penetration rates. For the signalised intersection, AVs were estimated to reduce the number of conflicts by 20% to 65% with AV penetration rates between 50% and 100%. For the roundabout, the number of conflicts was reduced by 29% to 64% (depending on the parameters used in the simulation) with the 100% AV penetration rate. In the roundabout, conflicts seemed to increase between baseline and the 25% penetration rate, but then decrease when moving toward higher penetrations.

Papadoulis, Quddus, and Imprialou (2019) created five simulation models (one for each working day of the week) for a 44 km long three-lane motorway section in England. Their simulation results show that the estimated traffic conflicts were reduced by 12–47% (25% ADF penetration rate), 50–80% (50%), 89–92% (75%), and 90–94% (100%). When interpreting these results, it should be noted that Papadoulis, Quddus, and Imprialou (2019) assumed that AVs could drive closer to their preceding vehicles than human drivers, enabling them to create vehicle platoons with other AVs.

Virdi et al. (2019) investigated the safety impacts of AVs through changes in the number of conflicts in the Geelong area of Victoria, Australia. Their simulation covered four types of intersections: signalised, priority, roundabout, and diverging diamond interchange. In the simulations, the AVs were introduced to the environment in 10% increments. The simulation results show that a 20% / 90% penetration of Connected and Autonomous Vehicles resulted in the following changes in the number of conflicts: +22% / -48% at the signalised intersection, −87% / -100% at the priority intersection, −62% / −98% at the roundabout, and +33% / -81% at the diverging diamond intersection. The signalised intersections show an increase in potential collisions for low penetration rates, while the priority intersections show an immediate and significant decrease in conflicts. It should be noted that Virdi et al. (2019) assumed that AVs adhered to a 0.5 m headway while manual vehicles drove with a significantly higher headway.

Virtual scenario-based experiments using Monte-Carlo techniques

Wang et al. (2017) tested virtual AD for two highway scenarios: an "obstacle in the lane" scenario and a "jam approach" scenario. In an obstacle-in-the-lane scenario, the probability of not having an accident was 28% higher with AD compared to manually driven vehicles. Furthermore, if an accident occurred, the mean velocity difference between the involved vehicles was 15% lower for the AVs. For the jam-approach scenario, AD reduced the accident rate by 28−49%, depending on the traffic jam speed (30 km/h vs. 0 km/h) and traffic speed variance (low vs. high). In this scenario, it is important to note that many accidents involving the target vehicle and included in the statistics are caused by another driver (e.g., driver to the rear) and thus, many of the accidents cannot be addressed by AD.

Fahrenkrog et al. (2019) used a traffic-based simulation approach to estimate the change in accident risk for AVs compared to manual driving. The simulations considered an exemplary AD on motorways in eight different relevant driving scenarios, including both expected positive and negative effects on safety. The expected mean change of accident rate per driving scenario was: Cut-in -83%, Traffic jam -40%, Rear-end accident -73%, End of lane −14%, Obstacle in the lane -40%, Highway entrance -49%, Minimal risk manoeuvre +2.6%–+48.4% (depending on braking strength). The authors noted that the effect in the driving scenario is only part of the potential safety effect, since in practice the function cannot operate under all conditions and is not always active. Hence, the paper also analysed the share of accidents related to each driving scenario within the ODD in the GIDAS database. This share varied between 67% and 95% for those driving scenarios for which reference data was available.

Counterfactual simulations

Scanlon et al. (2021) found in a counterfactual simulation study of 72 historic crashes (2008–2017) involving 91 vehicles in Chandler, Arizona, that Waymo AD did not cause any crashes (avoided all crashes when the Waymo vehicle was set as the at-fault (initiator vehicle; N=52) vehicle in the simulations). The Waymo AD avoided 82% of the crashes when it was set to be the not-at-fault/responder vehicle, while mitigating the effects of another 10%. All the remaining 8% (unavoided crashes) were in rear-end collision (the Waymo vehicle being struck from behind) scenarios. The virtual counterfactual safety assessment was done using a combination of real-world data collection, with Waymo vehicles driving through the collision locations of the historic crashes (collecting infrastructure, etc.), and virtual (sensor modelled) representation of the road users involved in the crash, as available from reconstructions.

Traffic simulations, accident re-simulations, counterfactual simulations & accident data

Rösener et al. (2018a) developed a framework including a combination of traffic simulation, accident re-simulations, and accident data for assessing the safety impacts of ADFs. The simulation-based estimated effectiveness of AD was scaled up for the whole of Germany with the help of the German in-depth accident database. The results indicate that a motorway chauffeur (at 50% market penetration) has a potential for reducing about 30% of all accidents on German motorways resulting in personal injury (equals 2% of all accidents on German roads). The urban robotaxi can avoid 26.5% of all accidents with personal injury within city limits at a market penetration of 50% (equals 17% of all accidents on German roads).

In L3Pilot, Bjorvatn et al. (2021) assessed the traffic safety effects of SAE Level 3 ADFs for passenger cars on motorways (motorway ADF including traffic jam ADF) and in urban areas (urban ADF). The safety impact assessment combined three types of simulations using different simulation techniques and input data (with the aim to compare the injury accident outcome in the computer simulations with manual driving and automated driving) and scaling-up of results to the EU27+3 level (all EU Member States, the United Kingdom, Norway, and Switzerland). The scaling-up process exploited road accident data from the European-wide CARE database, supported by information from national in-depth accident databases. Estimates were drawn for injury accidents per level of severity (slight, severe, fatal) and for AD penetration rates of 5%, 10%, and 30%. The results showed that AD has the potential to reduce the yearly number of injury accidents. For motorway AD, the reduction of all road accidents might not appear to be large (0.1%–1.2%, depending on the penetration rate and accident severity). However, considering the already high safety status of motorways, the reduction potential is large both on motorways in general (2.0%–19.0%) and within the ODD (3.8%–27.6%). For urban AD, the reduction of all road accidents was estimated to be 0.8%–10.2%, depending on penetration rate and accident severity.

8.2.2 Efficiency and environmental impacts

Traffic efficiency describes the capability of the road network to carry the traffic demand. Amongst others, it can be described in terms of average speeds, travel times, and throughput, which quantifies the number of vehicles passing on a road section per unit of time. In addition, the reliability of travel time in terms of travel time variation is of importance, as it describes how well the travel time can be estimated. Emissions and energy demand depend on vehicle characteristics such as mass, dimensions, engine and tyres, the prevailing conditions, and driver behaviour, especially accelerations (Ferrara, Sacone and Siri, 2018). The effect of aerodynamic drag increases quadratically with the increase in speed and is considerable at motorway speeds. Driving speed therefore has a large influence on energy demand and emissions. Traffic efficiency and emissions are somewhat related, as both benefit from a decrease in variance of speeds and accelerations, but there are also conflicts: efficiency is highest with shorter travel times at high average speeds, but energy demand is lower at moderate speeds.

AD has the potential to smoothen traffic flow by introducing more stable driving behaviour compared to human drivers. Generally, AD behaviour is expected to be more conservative compared to human drivers, leading to longer time gaps and smaller acceleration and deceleration values (Mattas et al., 2018). Furthermore, AD is expected to adhere to the speed limit. Lower and steadier driving speeds are expected to reduce emissions and fuel demand.

As L3 or L4 vehicles are not yet ubiquitous on real road networks, most of the research on the impacts of AVs on traffic efficiency and the environment has relied on simulation studies and field tests with ACC. It is generally expected that the longitudinal driving behaviour of L3 AD will be similar to that of ACC (Li et al., 2021), and that indications of AD impacts on longitudinal driving can thus be inferred from those studies. The existing literature provides a variety of results that depend largely on the assumptions made and the driving behaviour models used in the simulations (Calvert, Schakel and Van Lint, 2017, Do, Rouhani and Miranda-Moreno, 2019).

Also, most of the studies have assumed time gaps that are considerably shorter than those used in L3Pilot [1.6 sec, Bjorvatn et al. 2021], and although AD impacts have received some attention, most of the results relate to CAD. There seems to be a consensus that notable benefits for traffic efficiency can only be achieved with connectivity between vehicles. The commonest indicator of interest is throughput, but again, most studies have simulated a limited number of networks in terms of speed limits and traffic volumes.

Traffic simulation studies suggest that low-level AD in mixed traffic will initially have a small negative effect on traffic flow and road capacity, and improvements for traffic flow may only be seen at AD penetration rates above 70% (Calvert, Schakel and Van Lint, 2017), if at all. James et al. (2019) found small increases in throughput at penetration rates of up to 50% and decreases beyond. With larger, empirical time gaps, throughput has been found to be severely compromised already at low penetration rates. Shang and Stern (2021) used simulations to study throughput with a theoretical ACC system using parameters from the literature to investigate theoretical capability, as well as with calibration data from drives with commercially available ACC vehicles. They found an increase in throughput of 7% with an ACC time gap of 1.5 sec (theoretical controller) and decreases in throughput of 21%, 35%, and 28% with ACC time gaps of 1.0 sec, 2.2 sec, and 1.9 sec, respectively (calibrated ACC controller). Mattas et al. (2018) found a significant decrease in average speeds with increased penetration rate (time gap 1.6 sec).

Two relevant studies were found on emissions impacts of AD: Stogios et al. (2019) simulated an urban expressway (assumed speed limit 100km/h) with AD adopting cautious driving using a time gap of 2.1 sec. They found an increase in CO_2 emissions of 35% in high traffic conditions at 100% penetration rate. Mattas et al. (2018) simulated traffic on an urban ring road (assumed speed limit 80 km/h) with AD keeping gaps of 1.6 sec. They found an increase in CO_2 emissions of 2–6% in medium and high traffic conditions and a 2% decrease in low traffic demand conditions, with penetration rates of 60% and above. No change in emissions was found at low penetration rates (up to 40%).

Lateral driving behaviour of AD has been studied less, and current driver models have limitations in modelling lane changes by human drivers (HeWang and Chan, 2019). Therefore, the impacts of lane changes are not well known even though they cause disruptions to the traffic flow.

The L3Pilot project (Bjorvatn et al., 2021) provided estimates on the traffic efficiency and environmental impacts of L3 vehicles on a European level, taking into account representative speed limits, traffic volumes, fleet composition, and weather conditions. Scaling up of simulated effects was done per NUTS3 region based on hourly traffic and weather conditions within the regions' motorway networks over a period of 1 year. The results show that on the European level, with a 100% penetration rate of motorway ADFs fitted in passenger cars, vehicle emissions on motorways could be cut by 0.5%. Reductions of up to 17–19% per vehicle kilometre driven (VKT) were found at high traffic volumes, but most VKT are driven in low traffic conditions with a slight increase in emissions (up to 5% depending on road layout, speed limit, and traffic volume) resulting from the higher average speeds. Travel times and delay showed a slight increase (0.9% and 1.4% respectively) at 100% penetration rate on the European level.

For urban environments, simulations were conducted on two networks from two German cities. The impacts turned out to depend more on the characteristics of the network than on the AD penetration rate. Changes in CO_2 emissions per VKT were found to be negligible on one network but to drop by 4% and 9% on the other, at medium and high traffic levels and 100% penetration rate.

8.2.3 Mobility and transport system impacts

For an individual traveller, AD may affect their travel patterns for multiple reasons. First of all, AD may transform how the travel time is experienced, because it will enable using the time for other activities than driving. The time can be used for productive activities (e.g., working or taking care of personal tasks), leisure activities (e.g., keeping touch with friends and family), or as a time off (relaxing or resting). AD can also change the experience of travelling in other ways. For some travellers, AD may feel safer or more comfortable than manual driving (Nordhoff et al., 2020a). Others might not trust the AV to drive and may find it stressful. These changes in the travel experience are reflected in the acceptance and use of AD. Improved travel experience is linked to higher acceptance and expected use of AD (Kolarova and Cherchi, 2021, Lehtonen et al., 2021b).

It is important to consider that travel experience with AD depends on the performance of the ADF (e.g., how often TORs are issued), where it is used (e.g., in congested or free-flowing traffic), and who is using it (e.g., is it possible for the traveller to use the travel time for working). Therefore, also the impacts of AD on mobility can be specific to the system, users, and environments.

In other words, the above-mentioned changes in the travel experience with AD will influence how valuable the travel time is. The value of travel time is composed of the opportunity cost (typically how much salary could be earned if the travel time were used for working) minus the direct utility of the time spent travelling (Deserpa, 1971, Kouwenhoven and De Jong, 2018). Productive use of travel time could increase the utility of the time spent travelling, decreasing the value of travel time compared to manual driving, The expected decrease due to AD is often found in stated-preference surveys (De Almeida Correia et al., 2019, Kolarova, Steck and Bahamonde-Birke, 2019, Kolarova and Cherchi, 2021, Lehtonen et al., 2021b), even though the magnitude of impact and factors influencing it will need research. The most direct comparison is the effect of digitalisation on multitasking during public transport trips, which has been found to decrease the value of travel time and increase demand (Wardman, Chintakayala and Heywood, 2020).

In a person’s decision to travel, the positive utilities of travel time, such as having time off or experiencing the commute as a transition between work and home, might be more important than productive use of the travel time (Humagain and Singleton, 2020, Singleton, 2019). Travelers also look forward to engaging in leisure activities during AD more often than engaging in work (Nordhoff et al., 2020a). The value of positive utilities and leisure activities might be difficult to monetise, and therefore alternative concepts such as worthwhile travel time have been introduced (Cornet et al., 2021).

Depending on the level of automation, AD may also provide mobility to new user groups. Higher levels of automation, which would no longer require that the driver is able to take over the driving task, could provide mobility for those who currently are not able or willing to drive themselves.

New user groups will increase travelling by highly AVs, but the improved travel experience may also increase car use by current drivers (Bjorvatn et al., 2021, Lehtonen et al., 2021b). The effects of AD on travelling are often studied using simulation or models, where especially the decrease in value of travel time plays an important role (Kröger, Kuhnimhof and Trommer, 2019, Soteropoulos, Berger and Ciari, 2019). Part of the increase of AV travel can happen at the expense of public transport (Lehtonen et al., 2021a). Active travel modes might be less affected, because active travel implies positive utilities such as physical exercise or freedom of movement, which AD might not provide. Increase of travel with AVs is likely to be larger for some kinds of trips and traffic environments. AVs can especially make travelling in congested traffic or performing long-distance trips less unpleasant (Bjorvatn et al., 2021).

Changes in the amount of travel and travel patterns may have major implications for the transport system. Increased car traffic can worsen congestion and increase travel times, which may on the other hand decrease the attractiveness of car travel, but also increase interest in using the travel time for other activities. Increased traffic will challenge the sustainability of the transport system as the energy demand, emissions, and pressure to build more roads increase. AD may partly address these by increasing the efficiency of traffic (Bjorvatn et al., 2021).

Increase of VKT with different travel modes and in different traffic environments will also influence exposure to traffic hazards, potentially changing the number of crashes occurring. Increased vehicle kilometres and time spent travelling increase the costs of travelling, but the possibility to use the travel time in a productive or otherwise worthwhile way may compensate for these costs.

8.2.4 Socioeconomic impacts

Bjorvatn et al. (2021) investigate the socioeconomic impacts of SAE Level 3 AD for passenger cars on motorways (including traffic jam), urban roads, and for parking. The impacts are assessed in terms of safety, efficiency, and the environment at EU27+3 level (EU Member States, the United Kingdom, Norway, and Switzerland) for different AD penetration rates (5%, 10%, and 30%). The results indicate that for the motorway ADF, the net social benefits do not outweigh its costs. However, the safety impacts outside the ODD of the motorway ADF and the impact of AD on travel time costs show that the motorway ADF may well be expected to be beneficial from society's point of view. For the urban ADF, the expected net social benefits from accident prevention clearly exceed the social costs of its implementation. In addition, further safety impacts by utilising components in the urban ADF outside its ODD, and the impacts on the cost of travel time when driving with AD on rural roads, indicate monetary benefits of reaching the benefit-cost ratio of above 2.5. It is also likely that a package consisting of all types of AD (i.e., with motorway, urban and parking functionalities) would generate social benefits which exceed the social costs of installing such a package.

Andersson and Ivehammar (2019) studied the benefits and costs of automated trucks and passenger cars in terms of social generalised costs, external effects, and capital costs based on Swedish data. The study also considered the necessity of subsidisation of AD by the public sector. Using existing knowledge, manual driving (Level 2) as the baseline was compared with full automation (Levels 4 and 5), while Level 3 automation was assumed transitory. Rather than relying on long-term continuous forecasting, the study applied a "snapshot" approach to investigate the change in social generalised costs in the near (2025) versus distant (2040) future. The results indicate that the greatest benefits are from saved driver costs for trucks and decreased travel time costs for car drivers. However, capital costs may increase for both truck and car drivers by 22% and 36%, respectively. The impacts on reduction in fuel consumption and better safety are small. The study concludes that subsidies are not needed since the producers and consumers receive the major benefits and pay the costs. Impacts on mobility for the elderly, perceived safety and privacy with AD, infrastructure investments, land use, and congestion are not considered.

Kuang et al. (2019) assessed the safety, traffic, environmental, and industrial economic benefits of Intelligent Connected Vehicles (ICV) in China, and clearly detail the method behind their cost-benefit analysis. The focus is on the "flow" of annual benefits rather than a comparison of net present values. Business-as-usual is set as a baseline, where the transportation and automotive industry in China continue the current development trend, without any impacts of ICV. The results indicate total benefits of 13–24 trillion RMB in 2050, where savings on travel time and labour costs are important for all socioeconomic impacts.

Using data from China, Li (2021) performed a cost-benefit analysis of the impact of a new road policy which considered four different scenarios: 20% AVs with one exclusive lane, 50% AVs with one exclusive lane, 50% AVs with two exclusive lanes, and 80% AVs with two exclusive lanes. The exclusive AV lanes are beneficial in two scenarios and unbeneficial in two. For one AV lane, when the real penetration exceeds 15.5%, the exclusive AV lanes are beneficial, while for two exclusive AV lanes the penetration rate should be more than 46.1%.

Compostella et al. (2020) examines the costs of shared mobility services, vehicle electrification, and AV technology for users in the short term (2020) and long term (2030–2035) in the United States. Full automation is considered in the long term only. The findings show that AVs may make ride sourcing cheaper than driving one's own vehicle. Even if the manufacturing cost of AVs remains high, this cost will be minor when amortised over a service life of 400,000 miles. These findings are unchanged even with significant variations in assumed future battery and automation costs, electricity costs, vehicle insurance costs, maintenance costs, and overhead costs of ride sourcing providers. Compostella et al. (2021) build on an earlier study (Compostella et al., 2020) to include travel time costs for driving a personal vehicle or riding as a passenger. The study finds that ride sourcing becomes cost competitive with private AVs for longer trips, while pooled ride sourcing is generally the least attractive option for short trips. Vehicle automation and ride sourcing enable more productive use of travel time than driving and can result in significant reductions in travel time costs.

Zhong et al. (2020) examine the potential impact of AD on commuters' value of travel time (VOTT) in small and medium-sized metropolitan areas, concerning the spatial variability across urban areas, suburbs, and rural areas. A stated choice experiment is used to elicit potential changes in 1,881 auto commuters' valuation of travel time in AVs. The results suggest that the effect of AD on the VOTT is spatially differentiated. Riding in a private AV reduces the commuting VOTT of suburban, urban, and rural drivers by 32%, 24%, and 18%, respectively, compared to 14%, 13%, and 8% for riding in a shared AV.

8.3 Overview of research questions

Hi-Drive will address the large-scale impacts of AD and its enablers after market introduction, specifically on safety, energy demand, emissions, traffic efficiency, mobility, transport system, and society as a whole. Based on the state-of-the art review and the experience from L3Pilot, the following research questions are defined to cover these impacts (Table 8.1). It is worth noting that there is a linkage between some research questions set for vehicle data analysis (Chapter 7) and impact assessment research questions here, e.g., safe driving behaviour (test vehicle data analysis) and safety impact (in wider scenarios). This was made to allow easier reflection between field experiment results and the results addressing the impacts after market introduction.

Table 8.1: Overview of research questions on impact after market introduction.

High-level research question	Medium-level research question
What is the impact of AD and its enablers on safety?	What is the impact of AD and its enablers on safety in different driving scenarios?
	What are the indirect impacts of AD and its enablers on safety?
	What is the impact of AD and its enablers on safety at European level?
What is the impact of AD and its enablers on energy demand?	What is the impact of AD and its enablers on energy demand in different scenarios?

High-level research question	Medium-level research question
	What are the indirect impacts of AD and its enablers on energy demand?
	What is the impact of AD and its enablers on energy demand at European level?
What is the impact of AD and its enablers on the emissions?	What is the impact of AD and its enablers on emissions?
	What are the indirect impacts of AD and its enablers on emissions?
	What is the impact of AD and its enablers on emissions at European level?
What is the impact of AD and its enablers on traffic efficiency?	What is the impact of AD and its enablers on traffic efficiency in different scenarios?
	What are the indirect impacts of AD and its enablers on traffic efficiency?
	What is the impact of AD and its enablers on traffic efficiency at European level?
What is the impact of AD and its enablers on personal mobility?	What is the impact of AD and its enablers on travel patterns?
What is the impact of AD and its enablers on the transport system?	What is the impact of AD and its enablers on VKT?
	What is the impact of AD and its enablers on modal split?
What are the impacts of AD and its enablers from society's point of view?	What is the overall socioeconomic impact (net welfare effect) of AD and its enablers?
	How does AD affect the welfare of different stakeholders in society?
	How does AD and its enablers affect social equity?

9 Conclusion and outlook

As revealed by the set of research questions derived in this deliverable, Hi-Drive aims at addressing various challenges that currently hinder the deployment of high-level AD. Specifically, these are technical challenges that currently lead to a fragmented ODD with multiple interruptions and TORs, but also challenges related to the experience and expectation of the user influencing the experience of AD as a desirable, comfortable, safe, and easy-to-use technology. The broad focus of Hi-Drive is reflected in the six research areas; three of them cover the effects of AD and its enablers, while the other three examine user-related challenges. In total, 12 high-level and 44 medium-level research questions have been defined for user evaluation and 15 high-level and 34 medium-level questions for effects evaluation.

Within SP4 *Methodology*, the research questions presented in this deliverable are used as input for further definition of the methodology for Hi-Drive: they are considered when defining the data requirements (reported in deliverable D4.2 *Data for evaluation*) and the experimental design (D4.3 *Experimental procedure*), and when developing detailed analysis plans for user (D4.4 *User evaluation methods*) and effects evaluation (D4.5 *Effects evaluation methods*). Based on the requirements set by SP4 *Methodology*, SP5 *Operations* will collect the data needed for effects evaluation, and SP7 *Effects* will analyse it to answer the research questions on effects. In a similar way, SP6 *Users* will collect and evaluate data to answer the user-related research questions. At the end of Hi-Drive, the project results on the research questions will be presented in the deliverables of SP6 and SP7 (Figure 9.1).

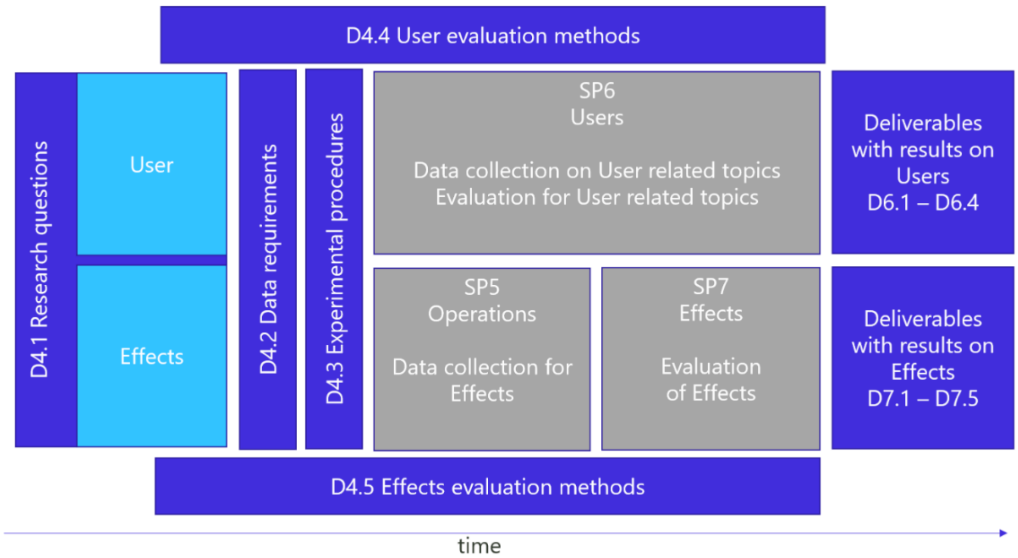

Figure 9.1: Simplified relation between the deliverable on research questions and other deliverables.

List of abbreviations and acronyms

Abbreviation	Meaning
ACC	Adaptive cruise control
AD	Automated driving
ADAS	Advanced Driver Assistance Systems
ADF	Automated Driving Function
AI	Artificial intelligence
AR	Augmented reality
AV	Automated vehicles
CAC	Conditionally Automated Cars
CAD	Connected and Automated Driving
CoP	Codes of Practice
dHMI	Dynamic human-machine interface
eHMI	External human-machine interface
GDP	Gross Domestic Product
GNSS	Global Navigation Satellite System
HMI	Human-machine interface
HMD	Head-mounted display
HUD	Head-Up Display
ICV	Intelligent Connected Vehicles
KPI	Key performance indicator
ML	Machine Learning
NDRT	Non-driving related task
ODD	Operational Design Domain
PI	Performance indicator
SAGAT	Situation Awareness Global Assessment Technique
SART	Situation Awareness Rating Technique
SDV	Software Defined Vehicles
SPAM	Situation-Present Assessment Method
TAM	Technology Acceptance Model
TOR	Take-over request
TPB	Theory of Planned Behaviour

Abbreviation	Meaning
UTAUT	Unified Theory of Acceptance and Use of Technology
VKT	Vehicle kilometre driven
VOTT	Value of travel time
VRU	Vulnerable road users
V2X	Vehicle-to-X communication

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