EXPLORING, DEVELOPING AND EVALUATING IN-CAR HMI TO SUPPORT APPROPRIATE USE OF PARTIALLY AUTOMATED CARS

DISSERTATION BY
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AUTOMATED CARS

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Abbreviations

ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistant Systems
ALC	Automated Lane Change
AP	Automated Parking
CC	Cruise Control
DIT	Digital In-car Tutor
GEE	Generalized Estimating Equations
GLMM	Generalized Linear Mixed Models (GLMM)
HMI	Human Machine Interface or Human Machine Interfaces
HUD	Head-Up Display
LKS	Lane Keeping System
LOA	Levels of Automation
NHTSA	National Highway Traffic Safety Administration
ODD	Operational Design Domain
SAE	Society of Automotive Engineers

*This dissertation is dedicated to my parents,
Arjan & Evi, who support me on all things big and small.*

Preface

I am proud to be able to present this thesis, which contains the core contributions of my PhD research. Working towards this thesis has been an extremely rewarding experience. The various projects and research opportunities have not only allowed me to push and develop myself academically, but also personally.

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Part I Introduction

Chapter 1

Introduction

Chapter 1. Introduction

Commercially available cars are increasingly equipped with multiple automated functions that simultaneously support lateral and/or longitudinal control. These systems partially and temporarily relieve drivers of their physical driving tasks (SAE, 2018)¹. As a large share of traffic accidents is attributed to human errors such as distraction (Brookhuis, De Waard, & Janssen, 2001; National Highway Traffic Safety Administration, 2008), removing the driver from the driving tasks may potentially increase traffic safety (Fagnant & Kockelman, 2015; Kuehn, Hummel, & Bende, 2009; Morando, Truong, & Vu, 2017). Furthermore, as an automated car may be able to accelerate and brake more smoothly and efficiently, driver comfort, fuel efficiency and traffic flow may be improved as well (Anderson et al., 2016; Annema, Van den Brink, & Walta, 2013; Davilla, 2013; Luo, Liu, Li, & Wang, 2010). However, studies show that automated car systems that still require some human interaction may actually evoke interaction issues that have a counterproductive effect on automation use and consequently traffic safety. Traffic safety may be severely impacted if drivers over-rely on the automation and use it outside its Operational Design Domain¹ (ODD) (i.e. in situations that the automation cannot function safely) (Parasuraman & Riley, 1997; SAE, 2018). On the other hand, if the automation is not used in situations that it can cope with (i.e. within its ODD), potential safety, emission and comfort benefits of automated driving may be lost. While this underreliance seems like a less urgent concern, it is still an important factor in the effectiveness and potential success of automated driving (Lee & See, 2004; Parasuraman & Riley, 1997). From this point further, we will refer to ‘appropriate automation use’² to indicate both using the automation when it can safely cope with the situation (within its ODD), and not using the automation when it cannot (outside its ODD). Correspondingly, using the automation when it can’t cope with the situation and not using it when it can cope is referred to as ‘inappropriate automation use’.

Particularly systems that require drivers to monitor the situation and decide when it is necessary to take back manual control are expected to pose significant interaction issues such as: erratic workload, decreased situation awareness, over- and under-trust, and inaccurate mental models³ (Endsley & Kaber, 1999; Martens & van den Beukel, 2013; Saffarian, De Winter, & Happee, 2012). While using these systems, the role of the driver (temporarily) shifts from manual operator to supervisor. This supervision is a highly demanding task. Not only do drivers need to be able to identify and understand the current and next actions of the automation, they also need to timely recognize whether it can cope with the situation, and prepare when it is necessary for them to take back control. Even more so, in the first place they need to know which automated functions

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1 See Section 2.1 for an overview of automation classification.

2 See Section 2.5 for an overview of appropriate automation use.

3 See Section 2.6 for a thorough discussion on the main interaction issues in automated driving.

are in their car, what they do and how they need to be operated. As drivers' understanding of the automation largely influences their ability to supervise and appropriately use it, they need to be supported in developing an accurate understanding of the automation's capabilities, and limitations (Boer & Hoedemaeker, 1998; Endsley, 2017; Heikoop, De Winter, van Arem, & Stanton, 2016; Lee & See, 2004; Stanton & Young, 2000).

Ideally, drivers should only be able to activate an automated system within its ODD, in which it should function completely safely, for example through geofencing. Furthermore, it should provide take-over requests well before reaching the end of its ODD so the driver has sufficient time to regain control (Martens & van den Beukel, 2013; van den Beukel, 2016). This way, drivers would not necessarily need to know the specific system limitations and situations in which it can (or cannot) function. However, technology is far from able to facilitate fully ODD restricted automation. While geofencing may be used to provide geographical boundaries for automation use, it does not take the traffic situation into account which may play a large role in the car's ability to safely drive automated. Considering the vast amount of varying traffic situations that one may encounter, it will be extremely difficult to classify in which situations the use of the car's automation needs to be restricted. Additionally, it will be hard to recognize these situations thus far ahead that sufficient time can still be provided to the driver to safely take back control, especially as critical driving situations may unfold within a matter of a few seconds (Damböck, Farid, Tönert, & Bengler, 2012; Gasser et al., 2012; Melcher, Rauh, Diederichs, Widloither, & Bauer, 2015; Vogelpohl, Kuhn, Hummel, Gehlert, & Vollrath, 2018; Zhang, de Winter, Varotto, Happee, & Martens, 2019). Even more so, even if we are able to provide full ODD restricted automation with sufficient take-over time, all car automation that still demands some human interaction requires the human to have a basic understanding of the available automated functions in their car, what these functions can do, and how they can be operated. Supporting drivers in understanding and safely using the automation in their cars is expected to be crucial for the foreseeable future (except for transport systems with highly specific ODDs which are isolated from other road users). Especially considering the facts that: automated cars without fully ODD restricted automation with sufficiently timely take-over requests are far from being released on the car market, all car automation up to and including level 4 requires some form of driver interaction, car-sharing will lead to drivers using different systems in different cars, and software updates within cars can lead to instant significant changes in functionalities.

Still, understanding the capabilities and limitations of the automated functions in one's car can be extremely challenging considering the wide variety of different combinations of automated systems that are currently entering the market (Abraham, Seppelt, Mehler, & Reimer, 2017; Teoh, 2020). Especially as individual car manufacturers use similar names for inherently different systems, and different names for similar systems (American Automobile Association,

2019). Furthermore, the vast variety of traffic situations make it difficult for drivers to recognize situations that may be outside the scope of the automation. Indeed, various studies have already indicated a lack of awareness and understanding of the automation in drivers' cars (Braitman, McCartt, Zuby, & Singer, 2010; McDonald, McGehee, et al., 2016; Onderzoeksraad voor Veiligheid, 2019). If drivers are not supported in understanding and supervising the automation in their cars, inappropriate automation use will lead to decreased traffic safety and loss of potential automation benefits.

The main goal of this research is to explore, develop and evaluate an in-car Human Machine Interface (HMI) to support drivers in understanding and appropriately using their car automation. The scope of this research explicitly focusses on support for non-professional drivers as they make up the majority of drivers, and do not receive any extensive training from for example an employer. Additionally, this research specifically focusses on partial car automation that either requires the driver to: continuously monitor the automation, or take back control within a relatively short timeframe after a take-over request. From here on, this will be referred to as 'partial automation' or 'partially automated driving'. This thesis describes the various studies that are conducted to investigate and develop driver support for understanding and appropriately using partial car automation. The current chapter will elaborate on the objective, approach and scope of this thesis.

1.1 Research objective

The main goal of this thesis is to explore, develop and evaluate an in-car HMI to support drivers in understanding and appropriately using their car automation. The new supervisory role of drivers in partially automated cars poses several challenges for drivers. Not only do drivers need to have an accurate understanding of their car's specific capabilities and limitations, they also need to be able to identify and understand specific driving scenarios, apply their knowledge about the automation, and decide whether it is safe to use the automation under these conditions (Muir, 1987; Rudin-Brown & Parker, 2004; Stanton & Young, 2005; Visser, Cohen, Freedy, Parasuraman, & De Visser, 2014). This is expected to be difficult for drivers considering the huge amount of different driving situations one may encounter, and the wide range of automated car functions with varying Operational Design Domains (ODDs) (i.e. circumstances for which the automated function is designed to operate in) that are currently integrated in commercial passenger cars. This needs to be addressed to ensure safe and appropriate automation use.

Before deciding to design any driver support it is crucial to be aware of how drivers are currently informed about their car automation, both before driving and through their car's HMI. Furthermore, it needs to be evaluated whether, and how, these current methods actually support

an accurate understanding and appropriate use of the automation. Investigating the current state will allow us to identify any issues that might hinder drivers' understanding and appropriate automation use, and consequently explore opportunities to improve the support. The research questions investigated in Part II of this thesis are therefore as follows: 1) *How are drivers currently supported in understanding and appropriately using car automation?* 2) *How may current driver support be improved to aid understanding and appropriate use of car automation?*

Following the results of Part II, a Digital In-car Tutor (DIT) is suggested in Part III as a potentially efficient way to support drivers in understanding and safely using their car automation, through guided learning and practice within their cars. During regular driving trips, a DIT can explain the various automated functions or systems in the car, and provide adaptive and situated information about the systems' capabilities and limitations. However, it is unclear how the suggestions for driver support from research question 2 can be practically incorporated into a DIT. Existing tutor interactions may provide inspiration and practical guidance for the design of a DIT. As driving instructors are the practical experts in the field of driver training and need to adapt to a wide variety of students and driving situations on a daily basis, Part III explores the tutor strategies of driving instructors, and how these can be used as inspiration for the design of a DIT. The first research questions of Part III are therefore: 3) *What tutoring strategies do driving instructors employ, and (how) are these adaptive to driving situations and students?* 4) *How can the design of a Digital In-car Tutor learn from the driver support strategies determined in research questions 2 and 3?*

Finally, the results of all prior studies are used to develop an adaptive Digital In-car Tutor (DIT) prototype in our driving simulator. It is explored whether, and how, a DIT is able to support appropriate and safe automation use. More specifically, use of the DIT should lead to more appropriate automation use compared to drivers' currently most used information methods (e.g. reading the owner's manual or brochure, and trial-and-error). This leads to the last research question: 5) *How does use of a Digital In-car Tutor affect automation use?*

Part IV reflects on the main findings of this research and provides recommendations for further research. As discussed, the overarching goal of this thesis is to explore, develop and evaluate an in-car HMI to support drivers in understanding and appropriately using their car automation. By combining the main findings of the studies conducted to achieve this goal, important lessons were learned to supporting driver's understanding and appropriate use of partially automated cars. These are encouraged to be used in further research and development on driver support in partially automated cars, in order to stimulate safe and efficient automation use.

1.2 Approach

As discussed in the previous section, the research goal of this thesis covers the exploration, development and evaluation of an in-car HMI to support understanding and appropriate automation use. To accommodate both the exploration, development and evaluation parts of this thesis, a variety of qualitative and quantitative research methods are used. These include online surveys, a literature review, an observation study and driving simulator studies.

Survey and literature review. The research question *How are drivers currently supported in understanding and appropriately using car automation? (RQ1)* is investigated through two methods: a survey and a literature review. First, a nationwide online survey is conducted in The Netherlands (Chapter 3). The survey addresses both the passive and active ways in which drivers receive information about the automation in their car. This includes how they were informed when they bought their car with partially automated functions at their car dealer, and how they search for information themselves (e.g. by asking a friend, searching online or reading the owner's manual). The method of an online survey is chosen as this is a fast and relatively low-cost way to reach a large and nationwide sample of car buyers. By including drivers all over the country, that bought their different types of automated cars at varying sales points, we are able to obtain a comprehensive overview of the current information provision in The Netherlands. As with most (paper and online) surveys however, systematic errors such as self-selection and partial-response may occur and need to be taken into account in the analysis and generalizability of the study (Bethlehem, 2008; Evans & Mathur, 2005; Vehovar & Manfreda, 2017). For example, drivers with a high interest in cars and technology may be more inclined to participate in our survey. These issues are therefore taken into account in the discussion of the results.

Another important place of information for drivers is the HMI within their car, and should be considered to answer the first research question. Drivers use this information directly to inform themselves about the current actions of the car, and to infer any required actions. A literature review is used to investigate the current state of both automation HMI in commercially available cars and of concept designs (Chapter 5). Hereby, we will identify both the current standards and the efforts that are made towards improvements. This literature review is therefore also used to address the research question: *(RQ2) How may current driver support be improved to aid understanding and appropriate use of car automation?*

Observation study. The following research questions are addressed through an observation study: *(RQ3) What tutoring strategies do driving instructors employ, and (how) are these adaptive to driving situations and students? (RQ4) How can the design of a Digital In-car Tutor learn from the driver support strategies determined in research questions 2 and 3?* During this observation study, driving lessons given by multiple driving instructors are videotaped and analysed. Both

qualitative and quantitative analysis methods are used in order to both evaluate existing tutor strategies and explore how these may be used in a Digital In-car Tutor (DIT) (Chapter 6). In the video analysis, all verbal tutoring is transcribed and a coding taxonomy is established to log and categorize all (non-)verbal tutoring. Both descriptive and (non-parametric) statistical analyses are then conducted to investigate any tutor patterns and how these are adaptive to the driving environment and the students. Semi-structured interviews with the instructors are used to further explore (additional) tutor strategies.

Driving simulator. In this thesis, driving simulator studies are used as a tool to evaluate the effect of current and new methods of driver support on automation (Chapters 4 and 8). More specifically, they are used to answer the following research questions: *(RQ1) How are drivers currently supported in understanding and appropriately using car automation?* and *(RQ5) How does use of a Digital In-car Tutor affect automation use?* A mid-fidelity driving simulator at The University of Twente is used to investigate these questions in two studies. This simulator includes a car mock-up and 180 degrees field of view screen,. The exact set-up of each study and the simulator herein is described as part of the respective studies. A simulator provides a safe environment to study the effects of certain information types on automation use. Furthermore, rare but critical scenarios can be included consistently across participants (De Winter, Van Leeuwen, & Happee, 2012). This is especially important for the studies in this thesis as difficulties with the car-driver interaction usually occur as the automation reaches the borders of its Operational Design Domain and driver intervention is (quickly) required.

Even though (fixed base) simulators cannot provide drivers with certain physical feedback, such as acceleration- and steering forces, many studies have shown their validity and value in driver behaviour research. Drivers show similar behaviour patterns while driving in both real cars and simulators. These include speed adaptation-, headway distance-, lane-keeping- and gaze patterns (Bella, 2008; Godley, Triggs, & Fildes, 2002; Risto & Martens, 2014; Underwood, Crundall, & Chapman, 2011; Wang et al., 2010). Similarly, studies like that by Walker, Hauslbauer, Preciado, Martens, and Verwey (2019) found that mid-range simulators like the one at the University of Twente already evoke a high sense of presence. While Poisson, Bourmaud, Denis, and Barré, (2020) saw more monitoring behaviour during automated driving in a real car compared to in a simulator, they did find similar reaction times. Still, it needs to be taken into account that while simulator data may have relative validity (showing similar patterns compared to on-road driving), it may not have absolute validity (Godley et al., 2002; Kaptein, Theeuwes, & van der Horst, 1996). This means that we may not directly compare the absolute values from the simulator to those of on-road driving.

In both studies, the automation use is first analysed through standard descriptive and parametric statistical tests. Additionally, variations of Generalized Linear Mixed Models such as Generalized Estimating Equations are used to be able to thoroughly assess longitudinal data while accounting for various possible confounding variables.

1.3 Scope

i-CAVE. This dissertation is part of the national i-CAVE programme which stands for Integrated Cooperative Automated Vehicles (www.i-cave.nl). I-CAVE is funded by the Perspectief program within the Dutch Research Council (NWO) (project number 14896). Perspectief supports cooperation between industry and academia to further develop technology necessary to address societal issues. The aim of i-CAVE is to combine technological aspects of cooperative and highly automated driving, while taking Human Factors into account for safe and efficient car interactions. I-CAVE consists of seven projects (Figure 1.1), which all have their own, yet interconnected, lines of research. The current dissertation is part of project 5 ‘Human Factors’. Project 5 studies how we can support safe interactions between: 1) drivers and their automated car, and 2) vulnerable road users and automated cars. This current thesis focusses on the former.

Figure 1.1. Overview of the various research sub-projects in i-CAVE. This dissertation is part of project 5: Human factors.

Partial automation. While most projects of i-CAVE aim towards the development of technology behind vehicle automation, there is still a lot of research that needs to be done concerning the driver-car interaction with various automated functions (with varying operational design domains and levels of reliability). As lower levels of automation are increasingly implemented in new consumer cars, there is a pressing need to address the many human factors issues to ensure safe automation use. Until automated driving is completely safe under all conditions, the user still plays an important role. Especially partial car automation can pose safety risks as drivers need to have an extensive understanding of the system’s capabilities and limitations in a wide variety of driving situations. Therefore, this dissertation specifically focusses on cars that require drivers to continuously monitor the automation and decide when it is necessary to resume manual control, or require drivers to take back control within a relatively short timeframe after a take-over request.

Initial automation use by non-professional drivers. The scope of this research is targeted towards non-professional drivers of partially automated passenger cars. We focus on non-professional drivers as they are expected to have the most difficulties in understanding their cars' automation as they likely do not receive any extensive formal training. Correspondingly, we focus on passenger cars. Finally, we mainly concentrate on the initial use period of the automation. This initial use period is arguably the most challenging for drivers as the majority of the learning takes place during this period (Beggiato, Pereira, Petzoldt, & Krems, 2015; Forster, Hergeth, Naujoks, Beggiato, et al., 2019). Therefore, drivers mainly need to be supported in learning to use the automation before and during the initial interactions (Beggiato, 2014).

1.4 Thesis outline

This thesis starts with an overview of automated driving including its history, classification and main human factors issues in **Chapter 2**. Next, **Chapter 3** describes a comprehensive survey on the way that car buyers are currently informed about car automation at their car dealer, and where they look up information themselves. As car sellers themselves of course have to be sufficiently informed and trained in order to be able to provide buyers with information, the second part of chapter 3 contains a survey among car sellers on the way that they are currently informed about car automation. Subsequently, **Chapter 4** investigates whether one of the most used information sources for drivers, an owner's manual, is actually able to support drivers in deciding when it is (not) safe to use the automation. The chapter reports on a video-based driving simulator study in which drivers were required to turn off the automation if they thought that it could not safely cope with the situation.

Regardless of whether drivers are informed about their car's automation before driving, all drivers are currently confronted with their car's HMI (i.e. the dashboard display) that presents information about the automation state and largely contributes to drivers' understanding and use of the automation. **Chapter 5** therefore explores how current HMI of both commercially available cars and research concepts inform drivers about their automated functions. Furthermore, it is explored how current HMI may be adapted to improve the understanding and appropriate automation use of drivers.

Combining the outcomes of the previous chapters, a Digital In-car Tutor (DIT) is proposed in **Chapter 6** to provide guided learning and practice during regular driving trips. An extensive observation study among driving instructors is conducted to explore existing tutor strategies that may be used in the design of such a Digital In-car Tutor. Furthermore, chapter 6 examines how a Digital In-car Tutor may need to be adaptive to the driver and the driving situation to facilitate optimal and situated learning. To be able to determine how tutor strategies of instructors adapt

to the driving situation in chapter 6, a classification of driving situations and their complexity is necessary. A classification of driving situations and their perceived complexity is therefore investigated in **Chapter 7**. Next, a DIT prototype is developed and evaluated in a driving simulator study which is described in **Chapter 8**. This chapter investigates the effect of a DIT prototype on appropriate automation use. Additionally, this chapter discusses whether, and how, a DIT may be used to improve appropriate automation use, and which elements need to be adapted or investigated in future studies.

Finally, the main findings of this thesis and recommendations for further research are discussed in **Chapter 9**. Additionally, this chapter includes the most important lessons learned to support driver's understanding and appropriate use of car automation. It is advised that these lessons are used in further research and development to stimulate the potential benefits of car automation and avoid negative effects of partially automated cars on traffic safety.

Chapter 2

Automated driving

Chapter 2. Automated driving

This chapter provides a thorough background on automated driving including its classification, history, potential benefits and expected interaction issues. In order to be able to effectively discuss automated driving, there needs to be a common understanding of its classification. Additionally, it needs to be clear what specific type (or level) of automation within this classification is used throughout this thesis. Section 2.1 therefore provides an overview of the various classifications of car automation, and discusses which of these classifications is used throughout this thesis. Furthermore, it is discussed what specific level of automation is addressed in this thesis⁴.

Automated driving has been in development for almost a century. In order to develop any driver support, it is important to be aware of the previous and current advancements in automated driving, and how these may affect the car-driver interaction. The history and most important milestones within automated driving are therefore reviewed in Section 2.2, followed by a discussion of the state-of-the-art in Section 2.3.

Section 2.4 describes the main expected benefits that drive the development of automated driving such as increased traffic safety and comfort. However, in order for these benefits to arise, drivers need to appropriately use the automation. That is, the automation should only be used in situations that it was designed for. Section 2.5 describes appropriate automation use in more detail. Without support, several interaction issues may arise in partially automated cars that have a direct impact on automation use and consequently traffic safety. These issues, as well as the need to support drivers' understanding of car automation in order to avoid them, are discussed in section 2.6.

2.1 Classification of automation

Automation can be described as a system or process that can operate without human intervention (Nof, 2015). There are many reasons to introduce automation. For example, to conduct work that humans cannot do or to make a task more efficient or safe. However, this doesn't mean that humans are completely disregarded with automated systems. On the contrary, human are necessary to build, maintain, supervise and even intermittently operate automated systems (Lee & Seppelt, 2012; Nof, 2015; Sarter, Woods, & Billings, 1997). Consequently, many types of automated systems exist, with different degrees of human involvement. As research and development of automation progresses, clear definitions of the different types and levels of automation are necessary to provide clarity in discussions. The following section discusses the most widely used definitions of automation levels, both in- and outside the automotive domain, and describes which definition is used throughout this thesis.

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4 See also Section 1.3.

2.1.1 Levels of automation

The initial descriptions of levels of automation (LOA) were mainly created outside the automotive domain. Most of these descriptions categorize automation on a unidimensional scale (Endsley, 1987; Sheridan & Verplank, 1978). For example, Sheridan and Verplank (1978) created 10 levels of automation ranging from ‘The human does it all’ to ‘The computer acts entirely autonomously’. While these unidimensional scales were concise, they lacked detail on the type of task that was automated. Several studies proposed to include a second dimension related to the task type. For example, Endsley and Kaber (1999) (Table 2.1) and Parasuraman, Sheridan, and Wickens (2000) (Figure 2.1) both introduced four task types that were (partially) allocated to either the human or computer. By attributing specific tasks to either the human or computer, the classification of automation became more fine grained.

Table 2.1.

Hierarchy of levels of automation as defined by Endsley and Kaber (1999).

Level of automation	Roles			
	Monitoring	Generating	Selecting	Implementing
1) Manual control	Human	Human	Human	Human
2) Action support	Human/Computer	Human	Human	Human/Computer
3) Batch processing	Human/Computer	Human	Human	Computer
4) Shared control	Human/Computer	Human/Computer	Human	Human/Computer
5) Decision support	Human/Computer	Human/Computer	Human	Computer
6) Blended decision making	Human/Computer	Human/Computer	Human/Computer	Computer
7) Rigid system	Human/Computer	Computer	Human	Computer
8) Automated decision making	Human/Computer	Human/Computer	Computer	Computer
9) Supervisory control	Human/Computer	Computer	Computer	Computer
10) Full automation	Computer	Computer	Computer	Computer

Figure 2.1. Levels of automation for independent functions as defined by Parasuraman et al., (2000).

At the start of the 2010s, several LOA classifications were developed specifically within the context of automated driving. The most commonly used classifications were developed by the German federal highway research institute BAST (Gasser et al., 2012), the National Highway Traffic Safety Administration (NHTSA, 2013a), and the Society of Automotive Engineers (SAE, 2014, 2018). The classifications show large overlaps (Table 2.2), even though the SAE classifications has six levels and the NHTSA and BAST classifications only have five levels. At the time of writing, the updated SAE classification is considered the standard and will be used throughout this thesis (National Highway Traffic Safety Administration, 2018; SAE, 2018) (Table 2.3).

In the classification by SAE, the term ‘Driving Automated System’ (DAS) is used to refer to the technologies (i.e. hardware and software) that together are capable of executing (parts of) the driving task. Such a system generally consists of multiple automated functions like Adaptive Cruise Control. The term ‘Automated Driving System’ (ADS) is used for the combined technologies that specifically allow for level 3 automation and up. According to the SAE classification, a Driving Automated System can be attributed to a particular level depending on four system characteristics. First, it is determined to what extent the lateral- and longitudinal control is automated. If the DAS only automates either the lateral or longitudinal vehicle control, it is categorised as level 1. If both lateral and longitudinal vehicle control are automated simultaneously the system is at least level 2. Second, it is determined whether the DAS also automates the Object and Event Detection and Response (OEDR). This means that it is able to monitor the driving situation, recognize and classify objects and situations, and prepare and execute an appropriate response. If the systems OEDR is fully performed by the system, even if it is only in very specific scenarios, it is at least level 3. Third, it is assessed whether the user or the system is the only fallback solution. Up to

and including level 3, the driver is the primary fallback solution. Some level 2 systems however may have the ability to perform an emergency fail mitigation by stopping in its lane with the car’s emergency lights on if the driver is no longer holding the steering wheel or watching the road (level 2) (Cadillac, 2018; Tesla, 2018). Last, it is determined whether the Operational Design Domain (ODD) of the system is limited (see next paragraph). The system is of level 5 automation if it is not limited to any ODD and the car can drive autonomously in any situation. It is important to note that the level of autonomy can vary according to the situation (with exception of level 5 systems). For example, a car may drive at level 4 autonomy on highways but only at level 2 autonomy in complex urban environments.

Table 2.2.

Levels of automation comparison between SAE, NHTSA and BAST.

Level	0	1	2	3	4	5
SAE	No Driving Automation	Driver Assistance	Partial Driving Automation	Conditional Driving Automation	High Driving Automation	Full Driving Automation
NHTSA	No Automation	Function- specific Automation	Combined Function Automation	Limited Self-Driving Automation	Full Self- Driving Automation	
BAST	Driver only	Driver Assistance	Partial Automation	High Automation	Full Automation	

Table 2.3.

Summary of levels of driving automation by SAE (2018).⁵

Level	Name	Narrative definition	DDT		DDT fallback	ODD
			Sustained lateral and longitudinal vehicle motion control	OEDR		
Driver performs part or all of the DDT						
0	No Driving Automation	The performance by the driver of the entire DDT, even when enhanced by active safety systems.	Driver	Driver	Driver	n/a
1	Driver Assistance	The sustained and ODD-specific execution by a driving automation system of either the lateral or the longitudinal vehicle motion control subtask of the DDT (but not both simultaneously) with the expectation that the driver performs the remainder of the DDT.	Driver and System	Driver	Driver	Limited
2	Partial Driving Automation	The sustained and ODD-specific execution by a driving automation system of both the lateral and longitudinal vehicle motion control subtasks of the DDT with the expectation that the driver completes the OEDR subtask and supervises the driving automation system.	System	Driver	Driver	Limited
ADS (“System”) performs the entire DDT (while engaged)						
3	Conditional Driving Automation	The sustained and ODD-specific performance by an ADS of the entire DDT with the expectation that the DDT fallback-ready user is receptive to ADS-issued requests to intervene, as well as to DDT performance-relevant system failures in other vehicle systems, and will respond appropriately.	System	System	Fallback-ready, user becomes the driver during fallback	Limited
4	High Driving Automation	The sustained and ODD-specific performance by an ADS of the entire DDT and DDT fallback without any expectation that a user will respond to a request to intervene.	System	System	System	Limited
5	Full Driving Automation	The sustained and unconditional (i.e., not ODD-specific) performance by an ADS of the entire DDT and DDT fallback without any expectation that a user will respond to a request to intervene.	System	System	System	Unlimited

⁵ DDT refers to ‘Dynamic Driving Task’ and includes both operational tasks (e.g. lateral- and longitudinal control) and tactical tasks (e.g. monitoring and maneuver planning). OEDR refers to ‘Object and Event Detection and Response’ and includes the monitoring task and the execution of a response (e.g. taking back control). ODD refers to ‘Operational Design Domain’ and includes the operational conditions for which the system is specifically designed to function. ADS refers to ‘Automated Driving System’ and includes all functions that together automate the driving task on a sustained basis. The term ADS is specifically used for systems of level 3 automation and up.

What is interesting to note is that these classifications of car automation do not necessarily allocate specific tasks to the automation or human depending on their strengths. It has long been recognized that both automation and humans have their own strengths and weaknesses, and can be utilized to complement rather than replace each other (Sheridan, 2012). For example, automated systems may be faster or more reliable in repeated manual tasks, while humans may be better in adapting to a wide range of dynamic situations. The classifications of automation however appear to allocate the tasks according to the current technical possibilities. As discussed in the introduction, this will lead to interaction issues as some levels allocate tasks such as prolonged supervision to the driver while this is particularly difficult for humans.

2.1.2 Operational Design Domains

Solely using the SAE levels to classify automation is insufficient, as systems that fall within the same level of automation can have significantly different Operational Design Domains (ODDs). SAE (2018) defined ODDs as *'The operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics.(p. 14).'* While the level of automation indicates whether a Driving Automated System has a limited ODD, it does not specify what the limitations of this ODD exactly are. It is therefore critical to specify the ODD when discussing and developing Driving Automated Systems. Consider for example two automated systems (A and B) that are both classified as level 1. During foggy weather conditions system A can maintain longitudinal control as it is radar-based, while system B cannot as it is camera-based. Elements that may be used to define an ODD include for example infrastructure type and complexity, weather conditions and traffic density (Czarnecki, 2018; Gyllenhammar et al., 2020; Koopman & Fratrik, 2019).

It is unlikely that ODD restricted automated systems, that drive perfectly within their ODD and provide sufficient take-over time, will enter the car market in the foreseeable future. This makes it crucial that drivers are aware of their system's ODD as it determines their responsibility and role in specific driving situations. This is especially important when the driver needs to monitor the system and is considered the primary fallback solution. If the driver does not realize that the car is reaching the limits of its ODD, he or she may not take back control (in time and/or safely) when necessary. Consequently, traffic safety may be compromised. It is therefore essential that ODD's are considered to design for safe and appropriate automation use.

2.2 A brief history of car automation

Although car automation has been a widely discussed research and development area in the last years, the interest in automated cars is far from new. Already at the beginning of the 20th century, researchers and engineers started working on car automation. One reason for this development was the high number of transport related deaths after the first world war (Kröger, 2016; Norton, 2008). New ways needed to be explored to make driving more safe. Car automation was seen as a possible technical solution for less accidents, while setting an example for desirable driving behaviour. This is illustrated by the film “The Safest Place” by Jam Handy in 1935 which shows a driverless car that perfectly follows the rules and does not make any human-like mistakes (US Auto Industry, 2009).

The first steps towards car automation were made in the 1920s and 1930s. During this time multiple remote-controlled cars were presented to the public such as ‘The American Wonder’ in 1925 (Engelking, 2017; The free lance-star, 1932). Although a driver was not required to be physically present in the car, it still needed to be operated by someone outside the car. By the end of the 1930s, the new concept of “guide-wire” led both research and public to turn away from remote controlled cars (Wetmore, 2003). Murtfeldt (1938) first wrote about such a “super highway”. This concept envisioned pre-determined roads with electromagnetic wire in them to guide cars. The car would drive itself on the dedicated highways while people would still be able to drive the car manually on any other roads. During the 1950s, “guide-wire” was further idealized in the media (LIFE, 1956) with the main benefits being the elimination of human error and the opportunity to socialize more while driving. Disney even produced an animated movie, “Magic Highway USA” (ArjanN, 2013), in which they show their vision of the development of highways and automated cars. The 1950s was not only a period of idealization of automated driving, also the first tests with controlled highway systems like guide-wire were conducted by RCA Laboratories (Quigg, 1960; RCA, 1958). Opposite to the guide-wire concept however, this was also the decade when Cruise Control was first introduced under the name ‘Speed-o-Stat’(Rowson Jr., 1954).

During the 1970s, both academia and industry stepped away from guide-wire due to new safety regulations and economical- and technical feasibility (Wetmore, 2003). The costs to adapt large parts of the infrastructure, and further develop the technology appeared too great. Simultaneously, microelectronics became more affordable and were more frequently implemented in passenger vehicles (Kröger, 2016). This shifted the focus towards developing cars with image processing functions (Tsugawa, Yatabe, Hirose, & Matsumoto, 1979). This way, they should be less reliant on infrastructure changes to facilitate automated driving. At the end of the 1970s the first proprioceptive based driver assistance systems such as Anti-lock braking system (ABS) entered

the market (Bengler et al., 2014). Proprioceptive based systems control vehicle dynamics based on internal vehicle data (e.g. acceleration). For example, in the case of ABS the internal data on wheel rotations and brake forces may be used to identify extreme braking behaviour and prevent the wheels from locking-up. During the 1980s increased efforts were made towards vision based autonomous driving in numerous projects such as PROMETHEUS, NAVLAB and NAHS, (Bengler et al., 2014; Kröger, 2016; Nagel, 2008; Thorpe, Hebert, Kanade, & Shafer, 1988). These projects laid the groundwork for the exteroceptive driver assistant systems that were introduced to the market in the 1990s and 2000s, such as Adaptive Cruise Control and Lane Departure Warning. These exteroceptive systems act upon detected external cues such as detected road markings or other road users. For example, in the case of Adaptive Cruise Control radar may be used to determine the distance to a car in front and control the car's speed to keep a set distance. While first exteroceptive driver assistant systems mainly provided information and warnings (e.g. Lane Departure Warning), systems introduced at a later stage automated parts of the driving task (e.g. Adaptive Cruise Control).

Starting 2004, the US Department of Defence issued the DARPA Grand Challenge to stimulate research and development of off-road autonomous vehicles (<https://archive.darpa.mil/grandchallenge/>). The DARPA Urban challenge of 2007 shifted the focus towards automated driving in urban environments. This challenge sparked renewed interest and research into autonomous driving outside the military domain. Two years later, the self-driving car project by Google started with the aim to research and develop full automation for passenger cars (Teoh & Kidd, 2017). While the previous projects were mainly research driven, Tesla was one of the first companies to announce the introduction of partially automated software and hardware for their commercially available cars in 2013 (Sperling, Van der Meer, & Pike, 2018). This stimulated other large car brands to increase their efforts towards the introduction of commercial automated cars.

In order to be able to drive in fully automated mode, it has been argued that the vehicle need to be able to communicate to other vehicles. For example to be able to directly anticipate and react to events that happen multiple cars ahead. The Grand Cooperative Driving Challenge (GCDC) in 2011 signified the start for increased efforts towards connected driving. In connected driving, the car communicates either to other road users (V2V) or the infrastructure (V2X) to be able to drive automated (Narla, 2013). Still, to obtain the most safe and reliable automated functions, projects have started to focus on combining vision- and connective technologies (Shladover, 2018), for example in the projects Ko-HAF (www.ko-haf.de) and SARTRE (<https://cordis.europa.eu/project/id/233683>).

2.3 State-of-the-art

Of all newly sold cars in The Netherlands in 2018, more than 90% included basic ADAS that take over a part of the driving task such as Cruise Control (BOVAG & VMS, 2019). While more advanced ADAS such as Adaptive Cruise Control and Lane Keeping Systems showed a sharp increase over the last years, they are still only standard in a limited amount of new cars. For example, Adaptive Cruise Control was integrated as a standard feature in only 16% of all newly sold cars (BOVAG & VMS, 2019). Still, the European Commission has agreed to make several safety focused ADAS mandatory in all cars that are sold after 2022 which include for example Advanced Emergency Braking, and Emergency Lane Keeping Systems (European Commission, 2019). Furthermore, level 2 automated cars, that take over multiple driving tasks simultaneously, are slowly entering the commercial market. In 2019, 8% of the newly sold cars in Europe included level 2 automation (Canalys, 2019). As partial automation is increasingly integrated in commercially available cars, drivers will need to be aware of the functions as they are mostly disengaged by default. Additionally, they need to be able to operate them appropriately.

Although Audi stated to have developed level 3 automation for their A8 model, this was eventually not fully implemented (Hetzner, 2020). The so called Traffic Jam Pilot would automate both longitudinal and lateral control in a very specific Operational Design Domain (Audi MediaCenter, 2017). It would only function in traffic jams (with ‘nose-to-tail’ traffic), at speeds below 60 km/h, on multi-lane highways and motorways. During automation, drivers would be allowed to take their feet of the pedals, hands of the steering wheel, and even temporarily have their eyes of the road during highway congestion. However, drivers would need to stay alert to some extent since they would need to be able to take back control when the car issued a take-over request. Although Audi eventually abandoned implementation of level 3 automation in the A8, several car manufacturers such as Mercedes-Benz and BMW have indicated to strive for actual implementation of similar systems by 2021 (Faggella, 2020). The difficulty of level 3 implementation mainly lies in the fact that it needs to be capable and reliable enough to allow drivers to take their eyes of the road, *and* provide take-over requests with sufficient time if it can no longer cope. Multiple car manufacturers such as Volvo have stated to ‘skip’ level 3 automation since they do not want to provide this function without a back-up if the driver does not (timely) take back control (Volvo Cars, 2017a). While others like Tesla advocate that level 3 is an important step to take towards full automation, they currently remain at level 2 (Lambert, 2016) while decreasing the allowed hands-off wheel time after serious accidents occurred (Olsen, 2018). Currently, trials with level 4 automation mainly include low-speed public transport concepts on predefined routes, and within extremely specific Operational Design Domains (ODD). Examples of pods include the WEpods in The Netherlands (<https://www.i-at.nl/iatnl>) and the Capri Pods in the UK (<https://caprimobility.com/>). At this point no commercially available car is equipped with level 3, 4 or 5 automation.

During the last decade, estimates for full car automation have been very optimistic. For example, Tesla expected full automation on highways by 2015 and on most roads by 2018 (Sperling et al., 2018). Morgan Stanley even anticipated complete penetration of fully automated cars by 2026 (Shanker et al., 2013). Currently however, predictions for full automation range broadly with some companies stating that it is just ‘a few years away’, while others estimate that it will take at least two more decades (Faggella, 2020). Even if full automation would become available within a few years, it will still take a considerable amount of time before the technology becomes affordable for the mass. Until then, drivers will have to interact with their vehicles as they reach the boundaries of their ODD.

2.4 Potential benefits of automated driving

Automated cars could provide multiple benefits for both drivers and society as a whole. The main potential benefits include: improved traffic safety and driver comfort, but also reduced fuel consumption and CO₂ emissions (Fagnant & Kockelman, 2015; Laurgeau, 2012; Tientrakool, Ho, & Maxemchuk, 2011; Van Wee, Annema, & Banister, 2013). The following section discusses these potential benefits.

2.4.1 Comfort

Car automation may positively affect driver comfort for several reasons. First, smoother braking, accelerating and steering behaviour can make the driving experience more comfortable for all passengers (Luo et al., 2010). Second, drivers are (temporarily) relieved from (some of) the physical driving tasks. Third, in situations when drivers are no longer required to monitor the situation and take back control swiftly if requested, they can engage in non-driving activities while traveling. For example, drivers may engage with other passengers, play games on their phone, finish some work or just rest (Large, Burnett, Morris, Muthumani, & Matthias, 2017; Pfleging, Rang, & Broy, 2016). Still, it is unclear whether particularly cars with partial automation will increase or decrease overall drivers’ comfort as the supervision may be very demanding. If the relief from the physical driving tasks does not outweigh the demand of the supervision task drivers may rather just completely drive themselves.

2.4.2 Fuel and emissions reductions

It has been assumed that automated driving will reduce fuel consumption and CO₂ emissions due to more smooth braking and accelerating patterns (Anderson et al., 2016; Davilla, 2013). Especially cooperative automated vehicles could reduce traffic jams as they require less space per vehicle and reduce the ‘harmonica effect’ as they are able to directly respond to events further ahead (Fagnant & Kockelman, 2015). However, recent studies have indicated that the

opposite might be the case through increased travel (Miller & Kang, 2019; Rodier, 2018; Wadud, MacKenzie, & Leiby, 2016). As drivers can (temporarily) start doing non-driving activities during their trip, such as working, their value of 'lost' time will go down (Auld, Sokolov, & Stephens, 2017). In other words, the price they would be willing to pay to reduce the duration of their trip goes down. Being stuck in traffic on one's daily commute becomes less bothersome if you can already start work, or even enjoy some leisure time. Not only could this lead to less resistance to take the car instead of public transport, it may also increase the overall travelled distance (Miller & Kang, 2019; Perrine, Kockelman, & Huang, 2020). Reasons to choose longer commutes and leisure trips might include higher paying jobs or high quality leisure facilities which are further away. Automated car sharing is suggested as a way to reduce the required number of automated cars (Bosch, Ciari, & Axhausen, 2016), but needs to be accepted and adopted by travellers to be effective, and does not necessarily lead to reduced kilometres travelled. .

2.4.3 Safety

By far the most important reason for developing automated vehicles however is to increase traffic safety. Many risk factors concerning humans as drivers have been identified that negatively affect overall traffic safety (Dingus et al., 2006; National Highway Traffic Safety Administration, 2008). These include behaviours such as drunk-, distracted- and drowsy driving, as well as speeding or tailgating (Dingus et al., 2006; Kengen & de Wit, 2012; National Highway Traffic Safety Administration, 2019). Studies like those by The National Highway Traffic Safety Administration (2008) have attributed the majority of crash causes to human error (Fagnant & Kockelman, 2015). It has therefore been suggested that by eliminating the human risk factors driving safety may be increased. Depending on the penetration rate, Fagnant and Kockelman (2015) expect a reduction in crashes from 50% to 90%. However, drivers are expected to still have to interact with their cars for the far foreseeable future. Even level 4 automation still requires some human interaction once the car's ODD limits are reached. The changing interaction between drivers and their car is expected to create multiple difficulties that may negatively impact automation use and consequently traffic safety (see chapters 2.5 and 2.6) (Onderzoeksraad voor Veiligheid, 2019). Appropriate (safe and efficient) automation use needs to be supported to be able to gain any of the automation benefits (Martens & van den Beukel, 2013).

2.5 Appropriate automation use

In order for any of the benefits of partially automated driving to be able to occur, use of the automation needs to be both safe and efficient. That is, the automation should not be used outside its Operational Design Domain (ODD) and should be optimally utilized inside its ODD. We will refer to this as 'appropriate automation use' throughout this thesis. Four types of automation use

can be distinguished (Figure 2.2). Appropriate reliance is the use of automation if it is indeed safe to do so (inside the ODD). Appropriate take-over refers to a driver switching, or leaving, the automation off when it is indeed unsafe to use the automation (outside the ODD). Inappropriate reliance describes the act of a driver using the automation when it is not safe (outside the ODD). In literature, this is also referred to as ‘misuse’ or ‘overreliance’ (Parasuraman & Riley, 1997). Inappropriate reliance has a direct effect on traffic safety. For example when a driver relies on the car to drive automatically, while in fact the car cannot cope with the current driving situation. Inappropriate take-over refers to a driver switching, or leaving, the automation off while it would actually be safe to use it (inside the ODD). This is also called ‘disuse’ or ‘underreliance’ (Parasuraman & Riley, 1997). While this would not directly pose any safety issues, it does hinder the adoption of car automation and any accompanying potential benefits. Considering the effects of both inappropriate reliance and inappropriate take-overs this thesis focusses on avoiding or reducing both.

Automation	ON	Appropriate Reliance	Inappropriate Reliance
	OFF	Inappropriate Take-over	Appropriate Take-over
		Within ODD	Outside ODD

Figure 2.2. Classification of the four types of automation use.

2.6 Human Factors issues in partially automated driving

Especially in the lower levels of car automation, the role of drivers shifts from operator to supervisor. In cars with level 1 or 2 automation, drivers have to monitor the situation and decide when it is necessary to take back manual control. While drivers do not longer need to continuously monitor the situation in level 3, they still need to be aware of situations that might be outside the automations Operational Design Domain (ODD) as they need to be able to take back control within a relatively short time span if a take-over request is issued. This shift towards automation supervision has long shown to be difficult for humans (Bainbridge, 1983; Parasuraman, Molloy, & Singh, 1993) and is expected to induce multiple Human Factors issues including: erratic workload, distraction, complacency, reduced situational awareness, uncalibrated trust and incorrect mental models (Casner, Hutchins, & Norman, 2016; Cunningham & Regan, 2015; Martens & van den Beukel, 2013; Saffarian, De Winter, & Happee, 2012). These issues should be addressed as they all directly impact appropriate automation use, quality of take-overs, and consequently traffic safety.

2.6.1 Erratic workload

The new supervisory role elicits periods of both low- and high cognitive workload for drivers. Workload may be low in monotonous or visually ‘boring’ driving situations that require little supervision, and can lead to distraction and inattention. Drivers already get distracted by many elements both in- and outside their ‘normal’ manually driven car. For example by their smartphones and entertainment systems (Covington, 2020; National Highway Traffic Safety Administration, 2013b; Weijermars et al., 2019). It is likely that distraction will increase when physical driving tasks are automated. Drivers have a tendency to engage in non-driving activities in partially automated cars, even if they are still required to monitor the driving situation (Carsten, Lai, Barnard, Jamson, & Merat, 2012). Besides distraction, long periods of low workload supervision can also lead to automation-induced complacency as shown through reduced error detection (De Waard, 1999; Parasuraman & Manzey, 2010; Parasuraman et al., 1993). When no errors have been detected for a long time, the threshold to identify something as an error becomes more conservative (Green & Swets, 1966; Wickens, 2002).

On the other hand, intense supervision during complex driving situations can cause high workload (Banks, Stanton, & Harvey, 2014; Jamson, Merat, Carsten, & Lai, 2013). Especially in level 1 and 2 systems that require the driver to continuously monitor the situation and decide when it is necessary to take back control (De Winter, Happee, Martens, & Stanton, 2014).

2.6.2 Situation awareness

Both low and high workload can contribute to lowered situation awareness of drivers. Using the commonly used definition by Endsley (2012) the situational awareness of drivers can be described as: perceiving the driving situation, understanding this situation, and projecting the status of this situation in the future. On one hand, low workload can negatively influence drivers’ situation awareness through distraction and inattention. Even if drivers are still required to monitor the situation, long periods of low workload may cause the driver to become inattentive or distracted leading to low situation awareness. Still, especially systems that explicitly allow drivers to have their eyes off the road are expected to severely impact situation awareness. Studies have already shown lowered situational awareness in drivers that were engaged in non-driving tasks for long periods of time (Stanton & Young, 2005). On the other hand, high workload may limit drivers’ situation awareness if they are unable to allocate their attention to all relevant traffic elements.

Lowered situation awareness has a direct impact on traffic safety in situations that require the driver to take-back control. During a take-over (request) the driver’s workload increases suddenly as (s)he has to regain situation awareness and react within a short period of time. This has been shown to reduce take-over quality as drivers with low situational awareness tend to compensate

for their delayed reactions through more intense braking and steering behaviour (Gold, Damböck, Bengler, & Lorenz, 2013; Gold, Damböck, Lorenz, & Bengler, 2013; Merat, Jamson, Lai, & Carsten, 2012; Rudin-Brown & Parker, 2004; Zeeb, Buchner, & Schrauf, 2016). Additionally, in cars with level 1 or 2 automation, the driver may not even recognize that the system cannot cope and manual driving is required.

2.6.3 Trust

Trust can negatively influence automation use in partially automated cars through two ways: over-trust and under-trust (Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003; Parasuraman & Riley, 1997). In case over-trust, drivers overestimate the capabilities of the automation and expect it to safely cope with more situations than it actually can (De Waard, 1999; Lee & See, 2004; Parasuraman & Riley, 1997). This may result in dangerous driving situations when drivers use, and rely on, the automation outside its ODD. Additionally, over-trust may lead to inattention and engagement in non-driving tasks, affecting automation use through lowered situation awareness (Popken, Krems, & Nilsson, 2009; Wickens & Carswell, 2012). For example, if a driver believes that the car can drive in automated mode without supervision on highways, (s)he will trust the car to do so and will consequently not (or only partially) monitor the situation on highways. This is particularly dangerous in cars with lower levels of automation that require constant supervision.

While under-trust seems less critical it can still be an issue for the effectiveness of automated cars (Lee & See, 2004; Parasuraman & Riley, 1997). If the driver does not trust the abilities of the car, (s)he might want to take back control more often than is necessary, or not use the automation at all. This hinders the potential comfort and physical demand benefits of automated cars and may even cause stress to the driver. Several recent surveys have indicated concern among the general public about driving in automated vehicles (Cunningham, Ledger, & Regan, 2018; Schoettle & Sivak, 2014).

Taking into account the two-fold effects of trust on system use, any car automation should attempt to balance the trust of the user. The trust of the user in the system needs to be calibrated to the actual capabilities and boundaries of the system, for example through training or physical driving experience (Lee & Moray, 1994; Muir, 1987; Walker, Boelhouwer, Alkim, Verwey, & Martens, 2018).

2.6.4 Mental models

One of the main underlying factors that influences all previously discussed issues is the driver's mental model about the automation. While various definitions of mental models have been proposed (e.g. by Rouse and Morris (1986) and Johnson-Laird (1983)), we adhere to the widely

used definition by Carroll and Olson (1987): “...a rich and elaborate structure, reflecting the user’s understanding of what the system contains, how it works, and why it works that way” (p.12). A driver’s understanding of the automation, or mental model, can affect automation use influencing a driver’s trust and situation awareness (Heikoop et al., 2016; Stanton & Young, 2000). Supporting an accurate understanding of the automation is crucial for safe and appropriate automation use (Martens & van den Beukel, 2013; Muslim & Itoh, 2019).

As described both in- and outside the automotive domain, the user’s understanding of the automation directly affects his or her trust, and consequently affects automation use (Beggiato & Krems, 2013; Cassidy, 2009; Körber, 2018; Lee & See, 2004; Sheridan, 2002; Stanton & Young, 2000). Overestimating the system’s capabilities leads to over-trust and consequently overreliance or misuse, while underestimating the capabilities leads to under-trust and disuse of the automation. This relationship between information assimilation and belief formation (i.e. understanding and belief about the automation), trust and automation use (specifically reliance behaviour) is illustrated in the trust model by Lee and See (2004) (Figure 2.3). If the mental model of a driver about an automated car system does not match the actual capabilities and functions of the system, the driver will be unable to make appropriate reliance decisions.

Mental models also directly influence a driver’s situation awareness and consequently automation use (Heikoop et al., 2016; Stanton & Young, 2000). In order to be able to correctly identify, understand and act upon the automation state (and current driving situation), drivers need to have an accurate understanding of the system’s functions and capabilities (Goodrich & Boer, 2003; Seppelt & Lee, 2007). This knowledge allows drivers to guide their attention to relevant elements of the automation and environment while supervising, and determine which (if any) action is necessary. Multiple studies have proposed that the comprehension of driving situations follows similar patterns as found in text comprehension such as the Construction-Integration theory (Beggiato & Krems, 2013; Durso, Rawson, & Giroto, 2007; Kintsch, 1998; Krems & Baumann, 2009). In the first phase, perceived information about the driving situation unstructuredly activates constructs in the long term memory, in our case elements in the driver’s mental model about the automation. In the second phase, the new information is integrated into the long term memory through repetition and pattern recognition as relevant connections are strengthened and simultaneously incompatible connections are weakened (Kintsch, 1998). These mental models are then used as a base to comprehend the current situation and select any actions.

An incorrect mental model can hinder drivers in accurately understanding the situation, and may create confusion about the automation state (i.e. mode confusion) and required actions by the driver (Sarter & Woods, 1995; Sarter et al., 1997). Mode confusion is when an operator believes that the automation is in a particular state, while in fact it is not. For example, when a driver thinks

that the automation is on while it is not. Consequently, the driver will not operate the vehicle while this is actually necessary. Several case studies have indicated mode confusion on the road when driving commercially available partially automated cars (Banks, Eriksson, O'Donoghue, & Stanton, 2018; Endsley, 2017a). Mode confusion (or loss of mode awareness) has been a long identified problem in human-machine interaction research, and has led to numerous critical events and accidents within for example aviation (Landry, 2012; Sarter et al., 1997), but also in partially automated vehicles (Onderzoeksraad voor Veiligheid, 2019)

Figure 2.3. Trust- and reliance model as defined by Lee and See (2004).

2.6.5 Current lack of automation understanding

Unfortunately, several recent studies have indicated a lack of awareness and understanding of drivers about the automation in their car (Braitman et al., 2010; Harms & Dekker, 2017; McDonald, McGehee, et al., 2016; Onderzoeksraad voor Veiligheid, 2019). The survey by McDonald, McGehee, et al. (2016) found a lack of knowledge among their participants about most ADAS systems such as Adaptive Cruise Control. Harms and Dekker (2017) showed a lack of understanding and usage of ADAS among business drivers. More strikingly, the large majority of the business drivers was unaware that their car was equipped with Adaptive Cruise Control. Similarly, Braitman, McCartt, Zuby, and Singer (2010) found that Volvo drivers used the

automated functions that were active by default (e.g. forward collision warning), but were unaware of the functions that were off by default (e.g. lane departure prevention). Finally, automated car functions are currently not a standard element of (Dutch) driving lessons as only around twenty percent of the cars at driving schools include Adaptive Cruise Control, six percent include a Lane Keeping Assistant System and less than one percent includes systems that simultaneously take-over longitudinal and lateral control such as Autopilot (Vlakveld; Wesseling, 2018) . If left unaddressed, the lack of knowledge and awareness of drivers about the automation in their car will have negative consequences for the proposed benefits of automated driving.

Considering all discussed human factors issues with partial car automation, it is crucial that drivers are supported in learning about, and appropriately using, the automation in their car. Otherwise, the potential benefits of automated driving will not take place and, more importantly, traffic safety will be compromised. The following part of this dissertation will provide insight in the way that drivers are currently informed about their car's automation. To this end, three individual studies were conducted to investigate the current driver support before- and while driving. The results of these studies were consequently used to explore and develop HMI opportunities to improve the driver support in part III of this dissertation.

Part II

**Current state of informing
drivers about partially
automated cars**

Chapter 3

Current state of ADAS information at car dealers

This chapter is based on:

Boelhouwer, A., Van den Beukel, A.P., Van der Voort, M.C., Hottentot, C., De Wit, R.Q., & Martens, M.H. (2019). How are car buyers and car sellers currently informed about ADAS? An investigation among drivers and car sellers in The Netherlands. *Transportation Research Interdisciplinary Perspectives*, 4, 1-19. doi: 10.1016/j.trip.2020.100103

The data of this study is freely available at:

www.OSF.IO/JQ37Y.

Chapter 3. Current state of ADAS information at car dealers

3.1 Introduction

In order to avoid misuse and disuse of partially automated cars, drivers need to have an accurate understanding of the system's processes, boundaries and limitations (Muir, 1987; Rudin-Brown & Parker, 2004; Stanton & Young, 2005; Visser et al., 2014). To achieve this, drivers need to be supported in creating their mental models so they match the actual car system capabilities (Riley, 1996). An important factor that impacts the current driver's knowledge about automated car systems is the information drivers receive during the car purchase process. The large US survey by Abraham, Reimer, and Mehler (2018) suggested that drivers are mainly reliant on themselves for getting information about ADAS. Most drivers get their information either through the owner's manual, or by trial-and-error practice while driving. Trial-and-error was the main way of learning ADAS systems in the qualitative study in the Czech Republic by Viktorová and Šucha (2018), the US survey by Jenness, Lerner, Mazor, Osberg, and Tefft, (2007), and among business drivers in the Netherlands (Harms & Dekker, 2017). In contrast however, the preferred way of learning about ADAS was through the dealership (Abraham et al., 2018). It is important to know if and how exactly non-business drivers are informed at car dealers, and how this may be improved. Especially as higher (self-reported) ADAS knowledge was found if the preferred learning method matched the actual learning method (Abraham et al., 2018). With the exception of a local study among US car dealers by Abraham, McNulty, Mehler, and Reimer (2017) indications of the way car dealers inform costumers remain mainly anecdotal. Are drivers mainly informed through verbal explanations, brochures or do they receive any practical training? On the other hand, in order for drivers to be properly instructed about the automated systems, clearly the sales staff has to be accurately informed as well. It is unclear how sales personnel of these systems are currently informed about the systems.

Two separate nationwide surveys were administered in The Netherlands to get an insight in the way both consumers and car sellers are informed about ADAS. The first survey, described in section 3.2, was distributed among ANWB members that purchased a car in the last two years. ANWB is the biggest membership association in The Netherlands. ANWB aims to represent the interests of its members in the areas of recreation, tourism, traffic and transportation, in the broadest sense of the word. Therefore they come up with a wide range of products and services all mobility and recreation related, such as consumer education, providing live traffic information and roadside assistance (comparable to the American Automobile Association). The goal was to investigate how consumers are currently informed about ADAS when purchasing a car with these systems. The second survey, presented in section 3.3, was distributed among brand car dealers and independent car dealers registered with BOVAG. BOVAG is a large Dutch trade organization

for mobility retailers. The goal of the second survey was to investigate how car sellers are being informed and trained about the latest ADAS in The Netherlands. The methods and results of these surveys will be discussed separately and consequently combined in the discussion section.

By looking at both the consumer and car seller perspective, this study provides a comprehensive overview of the way both consumers and car sellers are informed about ADAS in the Netherlands. The results can be used for the development of guidelines and standardization of consumer education on automated car systems. This way, the results of this study can further stimulate safe, effective and efficient use of the new automated car systems.

3.2 Consumer survey

The following section specifically describes the methodology and results of the consumer survey among ANWB members in The Netherlands. This survey aimed to get an overview of the way consumers are currently informed about ADAS when purchasing a new or used car.

3.2.1 Methods

Participants. A survey was distributed in January of 2019 in The Netherlands to a random selection of ANWB members that signed up on “denkmeemetdeanwb.nl”. By signing up to this website, participants indicated that they were interested in joining studies and surveys on transportation in general.

In total, 1241 started the online survey and 713 respondents fully completed the questionnaire and bought either a new (48.8%) or used (51.2%) car in the last two years. The average age was 59 years ($M = 59.0$, $SD = 12.0$) with the youngest respondent being 20 years and the oldest 85 years. The ratio of male to female respondents was skewed with 82.3% being male. The most bought car brands in the last two years by the respondents were: Opel (11.1%), Renault (8.8%), Peugeot (7.4%) and Ford (7.3%). The majority of the cars the respondents bought were built in 2016 or later (64.3%). 11.1% bought a car built in or before 2010. The majority of the participants indicated to use a car as their main mode of transportation (88.1%). Both the interest in general new technology and car technology was relatively high. 59.2% indicated to agree or fully agree with the statement: “I am interested in new technologies (for example gadgets and apps)”. 11.1% disagreed or fully disagreed while the rest remained neutral. To the statement: “I am interested in the newest technological developments in cars”, 62.4% said to agree or fully agree. 9.8% disagreed or fully disagreed while the rest was neutral.

The majority of the participants had Cruise Control (CC) (93.1%), while only 13 participants (1.8%) had Automated Lane Change (ALC) in their car. This small group size for ALC owners

needs to be taken into account when interpreting the corresponding ALC survey data. The amount of participants that had Adaptive Cruise Control (ACC) was lower at 22.6%. 24.1% indicated to have Lane Keeping (LK), while 19.4% had Automated Parking (AP). All 713 participants had at least one system in their car. Participants mainly received their car personally at the car dealer (89.2%). 2.8% received the car at home (1.4%) or at work (1.4%) with personal guidance of a salesperson. Only 0.8% got their car personally at the official car manufacturer. The remaining 7.2% indicated another way of receiving their car. These included buying their car from a private seller, or importing a car themselves.

Materials and procedure. The online survey was conducted through the survey website qualtrics.com. It took around 10 minutes for participants to complete the survey and participants could win one of three gift certificates of 10 euros. Although the survey was administered in Dutch, a translation was made for this paper which is available in appendix A.1.

The first section of the survey contained questions about the car of the participant. This included the car brand, model, production year and how/where they received the car. It also addressed which of the following automated systems were present in the car and how often they used it: Cruise Control (CC), Adaptive Cruise Control (ACC), Lane Keeping (also called lane centring) (LK), Automated Lane Change (ALC) and Automated Parking (AP). Each system was shortly described to the participant. The second section addressed the information participants had received about their automated systems at their car dealer. This included whether and when they received the information, and additionally, the mode and content of the information. Participants were further asked about their positive and negative experiences when receiving information on the automated systems. Lastly, participants were asked how and why they looked up information about the systems after purchase. The survey finished with several questions regarding the participant's demographics. These demographic questions included age, gender and education level.

Analysis. The goal of this survey, identifying if and how most car buyers receive ADAS information, could mainly be achieved through descriptive statistics. Both Chi-Square (nominal data) and Mann-Whitney tests (Likert-scale data) were used to study potential differences between drivers that bought a new or used car. To avoid Type 1 Errors due to repeated testing for similar survey questions, Bonferroni corrections were necessary. The new alpha-value was obtained by dividing the original alpha-value ($\alpha_{\text{original}} = .05$) by the number of comparisons (Cabral, 2008; Proschan & Waclawiw, 2000; Weisstein, n.d.).

3.2.2 Results

Unless otherwise indicated, the results in this section refer to the full sample of 713 participants that bought a car in the last two years.

ADAS use. CC and ACC were used frequently or always by around 75% of their owners, and LK and ALC systems by around 60%. Table 3.1 shows an overview of the frequency with which participants used the automation in their car. LK was used regularly or during every drive by 61.2% of the 173 LK owners, and ALC by 61.5% of the 13 ALC owners. LK was only used sometimes or never by 32.9% while ALC was only sometimes or never used by 23.1%. Of the 139 AP owners, only 12.9% used it regularly or always. The percentage of AP owners that never or only sometimes used the AP system was very high at 84.9%. Participants indicated more often to never use LK (17.3%), ALC (23.1%) and AP (48.2%) compared to CC (6.8%) and ACC (8.7%).

Table 3.1.

Overview of the question: “How often do you use the following systems?”. Answers were only considered of participants that had indicated to have the particular system.

How often do you use the following system? N(%)	Never	Sometimes	Regularly	Every time I drive	I don't know	N/A	Total
Cruise Control (N = 664)	45 (6.8%)	107 (16.1%)	221 (33.3%)	287 (43.2%)	1 (.2%)	3 (.5%)	664 (100%)
Adaptive Cruise Control (N = 161)	14 (8.7%)	28 (17.4%)	42 (26.1%)	75 (46.6%)	0 (0%)	2 (1.2%)	161 (100%)
Lane Keeping (N = 173)	30 (17.3%)	27 (15.6%)	17 (9.8%)	89 (51.4%)	1 (.6%)	9 (5.2%)	173 (100%)
Automated Lane Change (N = 13)	3 (23.1%)	0 (0%)	1 (7.7%)	7 (53.8%)	0 (0%)	2 (15.4%)	13 (100%)
Automated Parking (N = 139)	67 (48.2%)	51 (36.7%)	17 (12.2%)	1 (.7%)	0 (0%)	3 (2.2%)	139 (100%)

Receiving information. Almost a quarter (24.4%) (95% CI = 21.3, 27.8) of all respondents reported that they did not receive any information on any of the systems at the car dealer. It appears that more used car owners (34.0%) don't receive information about any of the automated systems compared to new car owners (14.4%). A Chi-Square test confirms a relation between buying a new or used car and receiving information on the automated systems ($\chi^2(1, N = 713) = 37.1, p < .001$). Table 3.2 shows an overview of the participants that did not receive information per system. Answers were only considered of participants that had the particular system (respectively

664, 161, 173 and 139 participants). Especially high percentages of the ALC (46.2%) and LK (48.9%) owners said that they did not receive any information on this system. However it must be considered that the group of ALC owners was very small with 13 participants. Of all the 713 participants, 48 (6.7%) (95% CI = 5.1, 8.9) said that they turned down any information from the car seller themselves. The main reason for turning down any information was prior experience with the system, either in their previous car or in the car of someone else ($N = 18$). Other reasons were: they wanted to look it up themselves ($N = 7$), they were not interested in the systems ($N = 4$) or they had knowledge and/or experience about technology in general ($N = 3$). The answers to the question “When did you receive information about the systems from the car dealer?” were evenly divided. A third received the information during the initial purchasing contact (33.1%), a third received it during the delivery of the car (32.5%), and the last third received it both during the initial purchasing contact and during the delivery of the car (34.4%).

Table 3.2.

Overview of new- and used car owners that did not receive information on a particular automated system. Example: of the drivers that bought a new car with cruise control, 26.5% did not receive information.

I did <i>not</i> receive any information on:	New	Used	Total
Cruise Control ($N_{Total} = 664, N_{New} = 310, N_{Used} = 354$)	82 (26.5%)	141 (39.8%)	223 (33.6%)
Adaptive Cruise Control ($N_{total} = 161, N_{New} = 119, N_{Used} = 42$)	28 (23.5%)	13 (31.0%)	41 (25.5%)
Lane Keeping ($N_{total} = 173, N_{New} = 145, N_{Used} = 28$)	41 (28.3%)	9 (32.1%)	50 (28.9%)
Automated Lane Change ($N_{total} = 13, N_{New} = 10, N_{Used} = 3$)	4 (40.0%)	2 (66.7%)	6 (46.2%)
Automated Parking ($N_{total} = 139, N_{New} = 94, N_{Used} = 45$)	24 (25.5%)	17 (37.8%)	41 (29.5%)

Content of received information. All participants that received information about at least one automated system ($N = 453$) were asked about the content of this information (Table 3.3). Half of the participants received extensive to very extensive information about the general functionalities (56.1%), and how to operate the system (55.5%). The capabilities and limitations (39.8%) as well as the hardware and technical functioning was discussed extensively to very extensively to 41% of the participants. The capabilities and limitations (9.5%) as well as the hardware and technical functioning (12.8%) were not discussed at all for around 10% of the participants, while only around 1% of the participants never got information about the functions (0.7%) or operating the system (1.3%). Mann-Whitney tests ($\alpha_{adjusted} = .0125$) were performed for each topic to investigate any differences in distribution between the new- and used car owners. Please refer to Section 3.2.1 on how the adjusted alpha value was determined. All topics showed different distributions between the two groups on the extent to which a topic was discussed (all $p < .003$).

Table 3.3.

Overview of the question “To what extent did the information you received cover the following topics?” ($N_{Total} = 453$, $N_{New} = 264$, $N_{Used} = 189$).

		Not at all	Little	Neutral	Extensively	Very extensively
General functionality	New *	0,0%	4,9%	35,2%	47,3%	12,5%
	Used *	1,6%	9,5%	38,1%	43,9%	6,9%
	Total	0,7%	6,8%	36,4%	45,9%	10,2%
Operating and handling the system	New *	0,4%	6,4%	35,2%	45,1%	12,9%
	Used *	2,6%	6,3%	39,2%	45,5%	6,3%
	Total	1,3%	6,4%	36,9%	45,3%	10,2%
Capabilities and limitations	New *	8,0%	13,3%	37,5%	30,3%	11,0%
	Used *	11,6%	13,8%	37,0%	33,3%	4,2%
	Total	9,5%	13,5%	37,3%	31,6%	8,2%
Hardware and technical functioning	New *	11,4%	12,5%	33,3%	33,0%	9,8%
	Used *	14,8%	13,8%	32,8%	33,9%	4,8%
	Total	12,8%	13,0%	33,1%	33,3%	7,7%

Mode of received information. All participants who claimed to have received information about (at least one) of the automated systems ($N = 453$) were asked how they received this information (Table 3.4). This was a multiple choice question where multiple answers could be chosen. The most common ways of informing were verbal explanation by the seller, (a referral to) the owner’s manual and brochures. 87.2% of the participants received verbal explanation. What is interesting is that only 8.8% of the participants has tried out the functions on the road with the seller. Furthermore, only 1 participant had an official training that consisted of both theoretical and practical training. Chi-Square tests ($\alpha_{adjusted} = 0.007$) confirmed that more new car owners received brochures ($\chi^2(1, N = 453) = 9.262, p = .002$). Similarly, more new car owners were referred to a website for information ($\chi^2(1, N = 453) = 7.637, p = .006$). As this was a question where participants could check multiple answers, we also looked at the most common combinations of ways that participants were informed. Around half of the participants (51.2%) solely received verbal explanation. The following most common combinations were all verbal explanations in combination with either a referral to the owner’s manual (11.9%), a brochure (6.6%).

Table 3.4.

Participants that answered “Yes” to the question “Did you receive information from the dealership in the following way?”.

	New (N = 264)	Used (N = 189)	Total (N = 453)
Verbal explanation by car seller	231 (87.5%)	164 (86.8%)	395 (87.2%)
Referral to the owner’s manual	72 (27.3%)	52 (27.5%)	124 (27.4%)
Brochure	69 (26.1%)*	27 (14.3%)*	96 (21.2%)
Trying out on the road	27 (10.2%)	13 (6.9%)	40 (8.8%)
Referral to a website	24 (9.1%)*	5 (2.6%)*	29 (6.4%)
By video’s shown by car seller	10 (3.8%)	1 (0.5%)	11 (2.4%)
An official training	1 (0.4%)	0 (0%)	1 (0.2%)

Looking up information. The most common ways participants looked up information on their automated systems themselves were through the paper owner’s manual (69.8%), the internet (30.4%), and the digital owner’s manual (29.9%). As people could choose multiple options, we looked at the most common combinations. Here we found that 28.9% of participants solely look up the information in their paper owner’s manual. The following most common combinations all included the paper owner’s manual in combination with either asking the car dealer (9.5%), searching on the internet (8.4%) and searching in the digital owner’s manual (7.3%). 7.6% only searched in the digital owner’s manual and 6.7% only searched on the internet.

Participants who looked up the information on the internet ($N = 217$) were asked on which websites they mainly searched. Participants were free to choose multiple options. Searching through a general search engine such as Google was used most often as 72.3% used this method. 59.5% of the participants said to look on the website of the car manufacturer, 33.6% looked on video sharing websites such as youtube.com, 20.3% looked on a car news website such as autoweek.nl and 19.4% looked on the website by ANWB, the Dutch traffic organization.

Customer experience. All participants that received information on any of the automated systems ($N = 453$) indicated how satisfied they were with the information on a 1-5 scale from “Very dissatisfied” until “Very satisfied”. The majority was satisfied or very satisfied (76.0%), while 18.3% was neutral and 5.7% was dissatisfied or very dissatisfied. There appears to be a slight satisfaction difference between new- and used car owners. Of the used car owners, 61.9% were satisfied and 13.8% very satisfied. Of the new car owners, 50% were satisfied and 26.1% was very satisfied. A Mann-Whitney test confirmed a difference in satisfaction between the new- and used car owners ($U = 22373, p = .038$).

Next, participants were asked to describe which aspects of the information they were specifically (dis)satisfied with. The main positive aspects about the given information were that it was clearly explained ($N = 172$) and enough time was taken ($N = 30$) by the seller. Other aspects that were named mainly considered the car itself ($N = 18$), friendliness of the staff ($N = 11$) and the demonstration ($N = 10$) or brochure ($N = 7$). Negative aspects of the provided information were: too little/ insufficient or no information ($N = 26$), too much information at once/giving information once is insufficient ($N = 10$), not taking enough time to explain the systems ($N = 9$) and not being able to try out the systems ($N = 3$).

3.3 Car seller survey

This section describes the methodology and results of the survey that was distributed to car sellers of official brand car dealers (OBD) and independent car dealers (ICD) in The Netherlands. This survey was conducted to gain insights in the way car sellers are currently informed about, and trained on, ADAS in commercial cars.

3.3.1 Methods

Participants. An online survey was distributed among both OBD and ICD members of BOVAG in July 2019. This distinction was purposefully recorded and analysed as it is expected that these different types of dealers have different information resources. It was stressed that this survey was specifically targeted towards the car salespersons within the dealerships. Any participant needed to have experience with direct sales contact with the customers, and sell cars younger than 12 years old as older cars are less likely to have ADAS. While a total of 468 participants completed the survey, 336 participants met all requirements and were used in the analysis. 141 participants worked at an official brand car dealer (OBD), while 195 worked at an independent car dealer (ICD). The large majority of the participants was male (97.6%). The average age was 48 years ($SD = 11.2$), ranging from 21 to 73 years.

A majority of the participants sold cars with parking sensors or cameras (97%), ACC (82.1%), Lane Departure Warning (79.5%), Emergency brake (75.6%), Blind Spot Detection (72.3%), Lane Keeping (72%), Automated Parking (67.9%), Live Navigation (67.9%), Distance Alert (61.3%) and Fatigue Recognition (61%). 42.9% of the participants sold cars with Intelligent Speed Adaptation. Only 12.2% sold cars with an Automated Lane Change system. 3 participants (0.9%) did not know whether they sold cars with any of these systems. 3 participants indicated that none of these systems were present in the cars they sold and were excluded from further analysis.

Materials. The survey took about 10 minutes to complete. Participants did not receive any compensation. Although the survey was distributed in Dutch, a translated version was created for this paper which is available in Appendix A.2.

The first part of the survey addressed the information that car sellers themselves *received* about (the latest) ADAS. Several questions asked the sellers from whom they received information, in what mode and what training they received. Furthermore it asked whether they looked up information about the automated systems themselves, why they did this, and where they looked up the information. Then, sellers were asked from whom they specifically expected to receive information about (new) automated systems. The second part of the survey addressed the information sellers *give* about ADAS towards customers. When do they provide (potential) customers with the information, what do they specifically address about ADAS and through which means? The last part of the survey asked the seller about their age, gender and job title.

Analysis. The goal of this survey was to identify if and how car sellers are currently informed and trained about ADAS. Similar to the consumer survey this goal could largely be studied through descriptive statistics. In order to investigate any differences between dealer type (OBD or ICD), Chi-Square (nominal data) and Mann-Whitney analyses were required. As in the consumer survey, corrected alpha-values were applied to analyse multiple related survey questions and control for Type 1 Errors. Again, the corrected alpha-values were determined by dividing the original alpha-value ($\alpha_{\text{original}} = .05$) by the number of comparisons (Cabral, 2008; Proschan & Waclawiw, 2000; Weisstein, n.d.).

3.3.2 Results

The following sections discuss the results of the distributed survey among both official brand car dealers (OBD) and independent car dealers (ICD).

Receiving information. 126 out of 333 participants (37.8%) (95% CI = 32.7, 43.3) indicated that they did not receive any (12%) or insufficient (25.8%) information about ADAS (Table 3.5). It appeared that less OBD sellers (8.5%) receive insufficient (or no) ADAS information compared to ICD sellers (59.1%). A Chi-Square test confirmed a difference between OBD and ICD sellers ($\chi^2(2, N = 333) = 88.1, p < .001$).

Table 3.5.

Overview of the question “Do you think that you receive enough information about ADAS (from your car manufacturer; importer; holding; nearby dealership or wholesaler) to inform customers?”.

	Official Brand car Dealers (OBD) (<i>N</i> = 140)	Independent Car Dealers (ICD) (<i>N</i> = 193)	Total (<i>N</i> = 333)
Yes, I receive sufficient information	128 (91.4%)	79 (40.9%)	207 (62.2%)
No, I receive insufficient information	9 (6.4%)	77 (39.9%)	86 (25.8%)
I receive no information	3 (2.1%)	37 (19.2%)	40 (12.0%)
	140 (100%)	193 (100%)	333 (100%)

54.1% (95% CI = 48.5, 59.5) of the sellers looked up ADAS information by themselves. They did this because: they thought the subject is interesting (54.4%), they didn’t receive enough information (31.7%), they didn’t receive the correct information (5%), or the information they received was too complicated and confusing (4.4%). Again, there appeared to be a difference between OBD and ICD sellers as 11.1% of the OBD sellers looked up the information because the information they received was insufficient, incorrect or confusing against 51.2% of the ICD sellers (χ^2 (1, *N* = 333) = 48.61, p < .001). Sellers looked for ADAS information in multiple places ranging from any relevant website (61.7%), video websites such as youtube.com (51.1%), the paper owner’s manual (48.3%), asking colleagues (40.6%), the digital owner’s manual (38.9%) and internet forums (33.3%). 4.4% looked up information in a different place. Only 3.9% requested information from a stakeholder organization, and the same holds for looking up information in an app (3.9%).

Figure 3.1 shows the results of the multiple choice question: “How do you receive information about ADAS?”. Most car sellers received information by trying out the functions on the road themselves (44.7%), or through a training by the car manufacturer, importer or wholesaler (42.9%) (95% CI = 37.6, 48.5). There appeared to be large differences between OBD and ICD sellers as 80.7% of the OBD sellers received this training against 15.5% of the ICD sellers. A Chi-Square ($\alpha_{\text{adjusted}} = .05/10 = .005$) confirmed this difference for both the training by car manufacturers (χ^2 (1, *N* = 333) = 140.65, p < .001), and those by the dealer’s location or holding (χ^2 (1, *N* = 333) = 12.95, p < .001). The same holds for the use of brochures as 37.1% of the OBD sellers received brochures, against 10.4% of the ICD sellers (χ^2 (1, *N* = 333) = 34.40, p < .001). Furthermore, OBD sellers more often tried out the functions themselves (53.6%) compared to ICD sellers (38.3%) (χ^2 (1, *N* = 333) = 7.612, p = .004). Last, more ICD sellers did not receive any information (31.6%) compared to the OBD sellers (3.6%) (χ^2 (1, *N* = 333) = 40.13, p < .001).

Figure 3.1. Overview of the question: “How do you receive information about ADAS (from your car manufacturer, importer, holding, nearby dealership or wholesaler)?”. Participants (N = 333) could choose multiple options. OBD: Official Brand car Dealers. ICD: Independent Car Dealers.

All participants that received training ($N = 158$) were asked about the availability, capacity and relevance of these trainings. 69.1% rated the availability as good or very good, and 27.2% as sufficient. Only 3.8% considered the availability to be insufficient. A similar trend is seen in the capacity of the trainings as 72.8% rated it as good or very good, 24.7% as sufficient and 2.5% as insufficient. The relevance of the training content to their daily sales job was considered good or very good by 69.7%, sufficient by 25.9% and insufficient by 4.4%.

All participants were asked from whom they wanted to receive information about ADAS ($N = 333$) (Figure 3.2). OBD sellers mainly wanted this information from the car manufacturers/importers (87.2%) and BOVAG (Dutch stakeholder organization) (17%). In contrast, the ICD sellers mainly wanted information from the BOVAG (58%), followed by car manufacturers/importers (38%) and wholesalers (36.4%). The majority of the sellers expected digital materials targeted at informing their sales personnel (64.9%) and half of the sellers (50.3%) expected digital information for the consumer that they could apply directly during the sale and delivery.

Figure 3.2. Overview of the question: “From whom do you want information about ADAS?”. Participants ($N_{\text{Total}} = 333$, $N_{\text{OBD}} = 141$, $N_{\text{ICD}} = 195$) could choose multiple answers. OBD: Official Brand car Dealers. ICD: Independent Car Dealers.

Giving information to customers. 23.4% of the car sellers (strongly) agreed that they do not have enough time to inform customers about ADAS (Figure 3.3). 26.7% (strongly) agreed that they do not have the right training or education. 38.1% (strongly) agreed to miss the required materials to provide ADAS information, and 21.3% (strongly) agreed that they do not have enough time nor resources to investigate ADAS themselves. ICD sellers appeared to agree more with the presented statements. Even with a rather conservative adjusted alpha ($\alpha_{\text{adjusted}} = .0125$) (Cabral, 2008; Proschan & Waclawiw, 2000), separate Mann-Whitney tests confirmed a relationship between the dealer types and level of agreement with each statement. (all $p < .001$).

56.7% of the participants often or always gave information about ADAS to customers (85% OBD versus 36.3% ICD), while 18.9% rarely or never gave information about ADAS (5% OBD versus 29% ICD). The main strategies of informing customers included: verbal explanation (85%), test drives (46.3%), and referring to the owner’s manual (37.8%).

Figure 3.3. Sellers' perspectives on providing ADAS information to customers. Sellers rated their agreement to the depicted statements on a scale from 1- strongly disagree to 5- strongly agree ($N_{\text{Total}} = 333$, $N_{\text{OBD}} = 141$, $N_{\text{ICD}} = 195$). OBD: Official Brand car Dealers. ICD: Independent Car Dealers.

3.4 Discussion

The goal of this study was to get a comprehensive overview how both car drivers and car sellers are currently informed about ADAS in The Netherlands. Our study extends consumer surveys like those by Abraham et al., (2018) and Viktorová and Šucha, (2018) by presenting the perspectives of both consumers and car sellers. Any identified gaps in informing consumers and car sellers about ADAS may be used to develop standardized information materials and -strategies.

3.4.1 Consumers

Our results show that almost a quarter of the drivers that bought a car in the last two years did not receive any information about their car's ADAS. This is a worrisome amount of drivers that left their car sales point without ADAS information considering the complexity and variety of ADAS. In the previous study by Abraham et al., (2018) in the US, only 12 percent of the participants did not receive any ADAS information at their dealership. However, during that study, the vast

majority of participants had bought a new car. In our study, used car owners were less likely to have received information compared to buyers of new cars. This may be a reason for the differences between our and Abraham's study. Furthermore, differences in sales points might be a potential explanation for the differences between new and used car owners, as used cars are more often bought at independent car dealers or private sellers. The different sales points do not have the same resources to provide the drivers with information, as is shown by our survey among car sellers. Unfortunately, the current survey did not allow us to investigate an effect of sales point on received information.

Drivers that did receive information, indicated that this mainly addressed just the basic handling and functionalities, but not the limitations and physical equipment. Especially knowing the limitations of ADAS is important as inappropriate use can have dangerous consequences (Capallera et al., 2019; Dickie & Boyle, 2009). Furthermore, only nine percent was able to try out the automated systems before taking the car home. This seems concerning considering the impact practice can have on a driver's ability to understand, accurately trust and safely operate ADAS (Beggiato & Krems, 2013; Ebnali, Hulme, Ebnali-heidari, & Mazloumi, 2019; Forster, Hergeth, Naujoks, Beggiato, et al., 2019; Larsson, 2012; Payre, Cestac, Dang, Vienne, & Delhomme, 2017). Ebnali, Hulme, Ebnali-heidari, and Mazloumi, (2019) found that simulator training allowed drivers to better decide when it was necessary to take back control of the automation. Similarly, Payre, Cestac, Dang, Vienne, and Delhomme, (2017) saw a decrease in reaction times and number of pedal interactions after extensive training and practice in a driving simulator.

Drivers mainly received their information from the paper owner's manual, a brochure or from their seller. When looking for information by themselves, they combine these resources with various websites. While online channels may be used to reach drivers and distribute standardized ADAS information, unregulated websites may be currently giving inaccurate ADAS information. That drivers mainly get their information from the owner's manual is consistent with the studies in the US by Abraham et al., (2018) and Jenness et al. (2007). Still, we must take the relatively high average age in our study into consideration as this age group may rely more on non-digital resources (Van Deursen, 2019)(i.e. paper manuals and brochures). As almost all drivers had personal contact with a car seller during the purchase and delivery of their car, this is a positive opportunity for the transfer of ADAS information towards the driver.

3.4.2 Car sellers

The results further show that almost forty percent of the car sellers did not receive (sufficient) information about ADAS. However, it is very important to correctly perceive 'the average percentage' outcomes of the study among sellers of cars, as large differences were found

between official brand car dealers and independent car dealers. This likely originates from the fundamental different market position of the dealers. Official brand dealers are formally linked to direct information sources from the manufacturers. Independent car dealers basically miss this primary information resource. While official brand dealers are mainly supplied with ADAS information by their car manufacturers and importers, independent car dealers less often receive the information from car manufacturers. They require multiple resources which include looking up the information themselves, asking other nearby official brand dealers and requesting information from their wholesaler. Another possible explanation for the differences between official brand car dealers and independent car dealers lies in the market penetration of current ADAS systems within The Netherlands. While simple systems like Cruise Control have been a standard feature in most new cars for over 10 years, newer systems like, Lane Change Assist have only just started to become standard features (BOVAG & VMS, 2019). Considering the fact that independent car dealers generally sell cars of a higher age (RDC, 2019), car sellers in these companies may not yet have been extensively confronted with the newer systems.

It appears that there is an opportunity to improve the information provision and training specifically towards independent car dealers. While a large share of the official brand car dealers receive some form of training on ADAS, this only holds for a small part of the independent car dealers. Any standardization of information needs to take the differences in information sources into account.

3.4.3 Consumers and car sellers

Many sellers do not have the necessary time, education, materials and other resources to use during customer contact and to investigate ADAS themselves. Consequently, almost a fifth of sellers rarely or never give ADAS information (5% for OBD and 29% for ICD). This is consistent with the finding from our consumer survey in which a quarter of the consumers indicated that they did not receive ADAS information. Although we cannot state causality, it may be that the lack of ADAS information for consumers is influenced by car sellers not receiving sufficient information. Car sellers indicated that their main methods to inform consumers are verbal explanations, referring to the owner's manual and explaining the functions during a test drive. This last method is inconsistent with the finding in our consumer survey as only a very small amount of consumers were able to test the functions during a test drive. Most car sellers expected ADAS information from the car manufacturers, importers and a stakeholder organization (in this case BOVAG). Furthermore, they preferred receiving ADAS information through digital brochures that targets them as sales personal. They would also like digital materials to use directly for the consumers during the sale and delivery of a car. These preferred information types should be considered in the development of standardized information to increase its acceptance and daily use.

3.4.4 Limitations

Some limitation need to be considered for this study. First, participants of the consumer survey were more than averagely interested in (automotive) technology. Also, participants signed themselves up on the website denkmeemetdeanwb.nl to be included in traffic related studies. It is therefore possible that a self-selection bias was present (Bethlehem, 2008; K. B. Rasmussen, 2016). On the one hand, participants may have been more inclined to asking ADAS related questions, evoking information from the car sellers. On the other hand, participants might have been more prone to decline information when they already had knowledge about ADAS. However, this does not seem very likely as only 2.9% indicated to have dismissed information because they had prior experience with, or knowledge about, ADAS. Therefore, if there was a self-selection bias, the ‘actual’ percentage of consumers that receives information of their car seller would be even lower than presented in this study. A second limitation is that the study was conducted exclusively in The Netherlands. Based on our results, we expect that consumers are less likely to be informed about ADAS in countries where used cars and independent car dealers dominate the automotive market. Still, our results may not be directly transferable to countries in which the structure of the automotive retail is significantly different. Especially considering the differences in automotive regulations across countries. Replication of our study is encouraged for countries with significantly different car retail structures. Therefore all surveys and data are freely available at www.OSF.IO/JQ37Y.

3.5 Conclusions

This study shows some important gaps in the current way of informing both consumers and car sellers about ADAS. A considerable amount of consumers does not receive any or insufficient ADAS information, with a specific lack of practice with the systems. This leads them to mainly rely on the owner’s manual and brochures. It is unclear whether reading the owner’s manual or a sales brochure is sufficient for drivers to create an accurate understanding of the automation, and know how and when to safely use it. It is therefore necessary to investigate whether, and how, such methods actually positively affect drivers’ understanding and use of car automation.

For car sellers, it appears that especially independent car dealers, struggle to receive standardized, updated and practical information about ADAS. Several options may address these issues. First, physical practice with ADAS may be necessary for both for consumers and car sellers as these may increase the understanding and safe use of ADAS (Panou, Bekiaris, & Toulou, 2010; Payre et al., 2017; Payre, Cestac, & Delhomme, 2015). The customer contact during sales and delivery can be an opportunity to include practical training and information. However, it is very important that car sellers are supported in this as a lot of car sellers already lack the time and resources to

inform customers about ADAS. Finally, the different preferred sources of information need to be taken into account for both the consumers and car sellers (Abraham et al., 2018).

In conclusion, major steps are required in the ADAS information provision for both consumers and car sellers. Especially as the automated systems that are introduced into commercial cars are expected to increase in complexity rapidly. Still, feasible opportunities for improvement and standardization were identified that may be implemented by either industry, stakeholder organizations and/or the government.

Chapter 4

Effect of theory training on take-over decisions in partially automated cars

This chapter is based on:

Boelhouwer, A., Van den Beukel, A.P., Van der Voort, M.C., & Martens, M.H. (2019). Should I take over? Does system knowledge help drivers in making take-over decisions while driving a partially automated car? *Transportation Research Part F: Traffic Psychology and Behaviour*, 60, 669-684. doi: 10.1016/j.trf.2018.11.016

The data of this study is freely available at:

www.OSF.IO/8RC4S

Chapter 4. Effect of theory training on take-over decisions in partially automated cars

4.1 Introduction

In the previous chapter, we determined that drivers are insufficiently informed and trained about the automation in their cars. The majority of drivers relies on their owner's manual or a sales brochure to learn about their car. (Eichelberger & McCartt, 2016; Jenness et al., 2007). It is unclear whether written system information that is currently given through owner's manuals is actually effective in aligning driver's mental models and car system capabilities. More specifically, does this method of driver instruction help drivers in deciding whether it is necessary to take back control of the car?

Using written system information as a means to inform drivers before driving an automated vehicle has engaged not only research, but also politics. Governmental and regulatory transport organizations have expressed their concern about whether additional training or licensing should be introduced for (partially) automated driving to avoid incorrect and inefficient use of such systems. Some countries, such as Sweden, have proclaimed that it is too early to make definite decisions about training and licensing (Swedish Transport Agency, 2014). However, others have already made some small alterations. In the Netherlands for example, it is allowed for driving schools to include practice session with support systems (CBR, 2015). The use of the support systems is also allowed to be tested additionally during the formal driving test, voluntarily, but the driver being tested also still needs to be able to perform all tasks manually. Currently, these mainly entail level 1 automated systems such as Cruise Control. While most countries do issue a requirement for trained drivers of automated test cars, official training guidelines for the use of commercial automated car systems are not available. Recommendations for additional education in automated driving are required.

This study explores the effect of written system information on the ability of drivers in a partially automated car to decide whether it is necessary to take back control. While many drivers do not receive any information about the automation in their car, drivers that do receive or look up information mainly get this through written system information (in owner's manuals or brochures) (Chapter 3). It is important to investigate whether written information actually even helps drivers in deciding if it is necessary to take back control of the car. It is hypothesised that by providing theoretical system information before initial system contact, the driver's mental model of the system is (at least partially) aligned to the actual system capabilities. Studying the effects of written system information on take-over decisions is important as it may provide insight into the required support for drivers in partially automated cars for a safe, efficient and acceptable driving

experience. The results of this study will be used for recommendations on the support required for drivers in partially automated cars. Furthermore, recommendations on the further development of these systems regarding driver support will be made to industry and academia.

4.2 Materials and methods

4.2.1 Participants

28 participants completed the experiment (18 male, 10 female). The average age was 38.64 years ($SD = 11.21$). All participants had normal or corrected-to-normal eye sight. The average years of driving licence ownership was 19.29 years ($SD = 10.86$). The average level of education was high in this study with 15 participants (53.6%) having a master's degree or higher, 8 (28.5%) having an associate or bachelor degree, and 5 (17.9%) having a high school certificate or lower level of education. Participants were selected and distributed beforehand on age, gender and driving experience to create two similar groups. Each group contained 9 men and 5 women. The mean age of the first group was 42.43 years ($SD = 13.04$), and in the second group the mean age was 34.86 ($SD = 7.73$). No significant difference was found in age between the groups ($t = 1.868, p = .076$). In the first group, drivers had an average of 22.71 years ($SD = 13.09$) of driving experience. The second group had an average of 15.86 years ($SD = 6.971$) of driving experience. There were no significant differences between the two groups on years of driving experience ($t = 1.73, p = .099$). None of the participants had any prior experience with automated car functions as a driver nor as a passenger.

4.2.2 Research design

The study used a between-participant design with repeated measures, and consisted of a video-based experiment that took place in a driving simulator. Participants were asked to imagine themselves driving a partially automated car. During these scenarios, the participant could indicate that they wanted to take back control of the car, by pressing a button on the steering wheel. As no real partially automated vehicle was available for testing, each driving scenario was video recorded prior to the experiment and displayed in a driving simulator for higher immersion.

The study contained two groups of 14 participants each. Group 1 received no information about the car system (the control group) while group 2 received system information about the partially automated car at the start of the experiment (the experimental group). The system information was based on automated systems that are expected to be available within a few years. The car was able to drive fully autonomously in urban areas; however some restrictions required the participant to intervene in certain situations. For example, the car was not able to perform reliably on steep slopes due to sensor limitations and would start to swerve. The system information is

explained in more detail in 4.2.3. Group 2 was also asked to take a knowledge test after reading the description to see if they understood and remembered the information provided.

23 video situations of a partially automated vehicle were presented in a random order for each participant. Due to a technical error, the software occasionally froze and skipped a scenario. Therefore, not all participants viewed the same amount of scenarios. This was taken into account during analysis, as is further explained in Section 4.2.6. All scenarios were categorized by the researcher before the experiment as ‘requires take-over’ ($N = 8$) or ‘does not require a take-over’ ($N = 15$). This was achieved based on the predefined system description of a partially automated car. To avoid the system being considered to be highly unreliable, the number of scenarios that required a take-over is lower than the ones that do not.

4.2.3 Materials

Questionnaire and knowledge test. Participants were asked to complete a questionnaire before entering the driving simulator about their main transport mode, car ownership and how often they drive a car. Furthermore, they answered the following four Likert scale questions on their attitudes towards automated vehicles. ‘What is your general opinion regarding automated vehicles on a scale from 1 (very negative) to 5 (very positive)?’. ‘How interested would you be in driving an automated vehicle on a scale from 1 (not interested at all) to 5 (very interested)?’. ‘How excited would you feel when driving an automated vehicle for the first time on a scale from 1 (not excited at all) to 5 (very excited)?’. ‘How scared would you feel when driving an automated vehicle for the first time on a scale from 1 (not scared at all) to 5 (very scared)?’.

Group 2 was asked to take a knowledge test after reading the system description. The knowledge test consisted of eight multiple choice questions based on the system description. This test was included to check if group 2 understood and remembered the system information before entering the driving simulator. One example of these questions is: “The adaptive cruise control: (A) automatically overtakes vehicles on the highway, (B) keeps 1.5 m distance to the preceding vehicle, (C) accelerates to the maximum speed if there is no other road user or obstacle ahead”. This knowledge test can be found in Appendix B.1.

System description. The system description (Appendix B.2) was based on partially automated car systems and capabilities that were expected to be available within two years. It assumed a vehicle able to drive autonomously in urban areas but still requiring intervention from the driver during some scenarios. The description on the automated car systems was provided in a similar way drivers currently mainly receive such information: through owner’s manuals (Eichelberger & McCartt, 2016). The system description was based on often recurring owner’s manual elements and therefore consisted of: a list of all the automated systems and their functionalities, the

hardware equipment, operational ranges, and requirements for optimal performance (including limitations). Since we are focussing on vehicles with a larger set of capabilities than current commercially available vehicles, a generally complex description may have been unavoidable. Most of the information was given in both written and graphical forms as is often the case in current manuals of non-automated cars. Examples of current owner's manuals can be found in Mercedes-Benz (2015); Tesla (2018) and Volvo (2018).

The information in the system description is considered to be mainly structural information. Structural information is conceptual and has the advantage that a small amount of content is required to cover a greater number of situations. Structural information refers to the explanations about internal systems, their functions, relations and boundaries (Eiriksdottir & Catrambone, 2011; Grotzer, 2002). An example would be: "The adaptive cruise control keeps a set speed while keeping a safe distance from its predecessor. It mainly uses the front cameras as input". Such information elicits mainly knowledge-based behaviour (Rasmussen, 1983). However, a disadvantage of this is that it requires high reasoning skills as it required drivers to deduce the information for specific situations. As a consequence, practical application of the information in driving scenarios may be (too) difficult. However, the alternative of procedural information (Eiriksdottir & Catrambone, 2011) is too specific for a dynamic driving task as it imposes very specific rules and often comes in the "if...then" form. Using procedural information would result in a very long list of rules for complex automated systems. It would then be very unlikely to capture all possible driving situations. Taking this, and current owner's manuals contents, into account the system information was mainly structural. Whether drivers are actually able to deduce the required information in practical driving situations is under investigation in this study.

Situations. While the participant was sitting in the driving simulator, 23 scenarios were presented in random order. Each scenario was categorized as requiring a take-over ($N = 8$), or not requiring a take-over ($N = 13$). Table 4.1 lists all scenarios and their descriptions. If the participants would push the button to indicate a take-over, the screen would turn black. Otherwise, the video would play until the end. This means that participants would see how the car dealt with the situation. The scenarios were chosen according to the seven main driving tasks defined by Rumar (1993): strategic tasks, navigation tasks, road tasks, speed control, traffic tasks, rule compliance and manoeuvring tasks. At least two scenarios per task were chosen, and some scenarios covered more than one specific task. Each scenario lasted between 30 and 90 s.

Table 4.1.

Experiment scenarios.

Scenario	Requires a take-over?	Description
1. Sharp curve	No	One sharp curve. No intersections. No other traffic. The car slows down to 30 km/h before entering the sharp curve
2. Cone	No	Straight road. No intersections. No other traffic. Large traffic cone is placed on the middle of the road. The car swerves around the cone
3. Roadworks	No	Roadworks. No intersections. 80 km/h road turns to 50 km/h road as indicated through traffic signs. The speed of the car automatically reduces to 50 km/h
4. Bike path	No	Straight road with a priority bike path crossing the main road. The car slows down and stops for two crossing cyclists
5. T-junction 1	No	Left turn at T-junction from priority to non-priority road. Oncoming cyclist that has priority. Car stops to give way to the cyclists and then turns left
6. Speed bumps	No	Straight 60 km/h road with 2 speed bumps. No intersections. No other traffic. Car drives 60 km/h
7. Pedestrian on road	No	Straight road. No intersections. Pedestrian walking on the right side of the road. The car swerves around the pedestrian
8. Left turn	No	Left turn on a straight 60 km/h road. One oncoming car that has priority. The car stops to let the oncoming car pass and then turns left
9. Non-signalised intersection	No	Straight road. Non-signalised intersection. One car approaches from the right and has priority. The car stops and lets the car from the right pass, then he continues to drive straight
10. T-junction 2	No	Left turn at T-junction from non-priority to priority road. Three cars approach from the right and have priority. The car stops and lets all the cars from the right pass, then he turns left
11. Traffic light	No	Intersection with traffic lights that turn red upon arrival. The car stops and continues to drive straight after the light turns green
12. Lane merge	No	Straight road which merges with the adjacent lane. No intervening traffic. The car merges into the adjacent lane before the end of the lane
13. Straight road	No	60 km/h straight road. No intersections. No traffic
14. Tunnel	Yes	Straight road through a short tunnel. The car swerves outside its lane because it has difficulties detecting road lines correctly on slopes
15. Crosswalk	Yes	Straight road with a pedestrian crossing. A pedestrian has the intention to cross. The car does not detect road markings other than lane indication, and does not stop for the pedestrian
16. Dead end	Yes	Straight road into a dead end. The car slows down, stops and does not re-route
17. Traffic controller	Yes	Straight road. No intersections. A traffic controller on the side of the road indicates the car to stop. The car does not recognise human gestures and continues to drive straight

Scenario	Requires a take-over?	Description
18. Small object	Yes	Straight road. No intersections. No traffic. A small object lies in the car's lane. The box is too low for the car to detect and drives over the object
19. Stranded vehicle	Yes	Straight road. No intersections. No traffic. A stranded car with its emergency lights on is blocking the road. Because the lanes have continuous road markings, the car will not overtake the vehicle and continues to wait behind it
20. Dirt road	Yes	Straight concrete road merges into a dirt road. No intersections. No traffic. The car does not detect the dirt road as a road and stops before it without re-routing
21. Zone end	Yes	Straight road that turns from a 50 km/h to a 80 km/h road. This is indicated through an 'end of residential zone sign'. The car only detects standard road signs and continuous to drive 50 km/h

Note. It was necessary to take back control of the car if: (1) traffic regulations had to be violated; (2) the car could not continue its predefined route; (3) the car could not avoid damaging something or harming someone.

All scenarios were filmed on and around the campus of the University of Twente, representing typical urban driving situations. All scenarios were filmed from a manually driven car. To avoid effects of the personal driving style of the driver, a cautious (sometimes called defensive) driving style was used for all scenarios. This included set stopping distances, deceleration rates, acceleration rates and maximum lateral forces (Karjanto et al., 2017). The driver was able to monitor his driving style live through a device called the AUTOAccD by Karjanto et al. (2017). Some examples included: driving towards and stopping for a traffic light, passing a non-signalised intersection and avoiding a small obstacle on the road. Figure 4.1 shows an example scenario in which the car needs to cross a busy bike lane on which cyclists have right of way. As the car detected the priority sign and the passing cyclists, the driver did not need to take over.

Figure 4.1. Example scenario from the experiment. In this case the car approaches a busy bike lane in which cyclists have priority. The car detects both the priority sign and the cyclists, and brakes in response. The driver does not need to take over.

University of Twente driving simulator. The experiment took place in the University of Twente driving simulator (see Chapter 1.2). As this is a video-based study regarding a partially automated vehicle, participants were not required to steer or use the pedals. However, they did have to press a button on the steering wheel to express their desire to take back control from the car's automated system. The program used to display the scenarios and record data from the simulator was Psychopy (Peirce, 2008).

4.2.4. Variables and measures

The main independent variable in this study was system information. Group 1 (the control group) did not receive any system information, whereas group 2 was asked to read and memorize the system information before entering the driving simulator. Furthermore, the general attitudes towards automated vehicles were assessed and controlled for during the analysis.

During this study, several dependent variables were logged to investigate the alignment between the driver's mental model and simulated automation capabilities. First of all, the take-over decisions of the participant (take-over or not) were measured and it was recorded whether these decisions were appropriate with regard to the scenarios. A decision deemed to be appropriate when the situation requirement (i.e. a necessity to take-over or not) matched the decision of the driver. Deciding on a take-over when a scenario was classified as 'requires a take-over' was appropriate, as well as relying on the system when a scenario was classified as 'does not require a take-over'. Deciding to take-over when it was unnecessary was considered to be an inappropriate decision, as well as when the participant failed to indicate a take-over if it was required. The total take-over score was calculated for each participant with the appropriate decisions as a percentage of the total number of scenarios presented. Applying this strategy, both a repeated measure and an average score for take-over decisions per participant were obtained. In order to be able to investigate the scenarios individually, they were randomized for each participant. However, when participants chose to rely on the car, and not push the button, they would see how the car coped with the situation. This feedback may have resulted in a learning effect, therefore the take-over decisions were also studied over time.

Participant were asked after each scenario why he or she decided to take over or rely on the car. The answers to this question were explored qualitatively, in order to explore what triggered participants to decide to take over or rely on the car. For the same reason, all comments the participants made during the experiment were logged.

4.2.5 Procedure

Each participant was individually welcomed in the driving simulator room and received general written information about the project. All participants participated voluntarily, and the procedure for the experiment was explained beforehand. It was explained in an informed consent that they could end the experiment at any time without giving a reason and without negative consequences. After signing the informed consent, the participant was asked to fill out a survey about their demographics and attitude towards partially automated driving. Group 1 could then go directly to the testing part of the study. Group 2 was asked to thoroughly read and study a system description for 15 min. Group 2 was informed that they needed to carefully study the information as they would need to answer some questions about the information before entering the driving simulator. After reading, participants in group 2 filled out a knowledge test that consisted of eight questions. These questions directly reflected the content of the system description to see if they understood and had memorized it. After the system description test, each participants was seated in the driving simulator and the task was explained. The task of the participants in the driving simulator was the same for both groups. Participants were asked to indicate whenever they thought or anticipated that the car could no longer cope with the situation, and they would take back control from the car if they were driving it, by pressing a button on the steering wheel. Participants were told that the car could not cope with a situation if: (1) traffic regulations had to be violated; (2) the car could not continue its predefined route; or (3) the car could not avoid damaging something or harming someone. After deciding to taking over or when the video finished, the screen would go black. After each scenario, the researcher would ask the participant why he or she decided to take back control or rely on the car. It was not indicated to the participant whether their action was considered appropriate or inappropriate. Finally, each participant was compensated for his or her time and effort with a €10 gift voucher.

4.2.6 Data analysis

This study uses a repeated measures design with a between factor of instruction. The decisions of the participants were categorized as ‘take-over’ or ‘no take-over, and ‘appropriate’ or ‘inappropriate’. First, descriptive statistics about the participants and the main measures were calculated. A Generalized Estimating Equations (GEE) (Liang & Zeger, 1986) procedure was used as most of the procedures’ characteristics fit the study’s data. This procedure assumes that the responses are not independent which is necessary for the repeated measurements (Pennsylvania State University, 2018). Furthermore, it is mainly used for longitudinal non-parametric and categorical data (Stupica, 2011), and can deal with uneven repeated measures. IBM SPSS version 24 was used for the analysis.

4.3 Results

4.3.1 Questionnaire and knowledge test

More than half of the participants ($N = 18$) (64.3%) stated their general opinion on automated vehicles to be either positive or very positive. 32.1% ($N = 9$) of the participants indicated a neutral attitude towards automated vehicles, while one of the participants listed a negative attitude. None of the participants indicated a very negative attitude towards automated vehicles. On the scale from 1 (very negative) to 5 (very positive) the mean scores were 3.64 ($SD = .93$) in group 1 and 4.00 ($SD = 0.68$) in group 2. A Mann Whitney test did not show any significant differences in attitude scores between the groups ($U = 74.5, p = .25$).

26 of the participants (92.9%) indicated to be moderately or very interested to drive an automated vehicle, while the rest indicated their interest to be neutral. None of the participants indicated to have little or no interest at all in driving an automated vehicle. The mean interest score (on a scale of 1 = no interest at all, to 5 = very interested) was 4.57 ($SD = .51$) in group 1 and 4.29 ($SD = 0.73$) in group 2. A Mann Whitney test did not show any significant differences in interest scores between the groups ($U = 78, p = .30$).

26 of the participants (92.9%) expected to be either moderately excited or very excited when driving an automated vehicle for the first time. One participant expected to feel neutral and one participant expected to not feel very excited. On a scale of 1 (not very excited) to 5 (very excited), group 1 scored their expected excitement during a first drive in an automated car on average 4.64 ($SD = .50$) and group 2 scored on average 4.21 ($SD = .89$). A Mann Whitney did not show any differences on this item between groups ($U = 72, p = .178$).

When asked how scared they would expect to feel during a first drive in an automated car, 5 participants (17.9%) said they would be very or moderately scared, 9 participants (32.1%) said to feel neutral, and 14 participants (50.0%) would be not very scared or not scared at all. Rated on a scale from 1 (not scared at all) to 5 (very scared), group 1 has an average score of 2.57 ($SD = .85$) and group 2 has an average score of 2.61 ($SD = .99$). No differences between groups were found on this item with a Mann Whitney test ($U = 97, p = .961$).

The knowledge test for group 2 consisted of eight multiple choice questions that were directly related to the system description that was provided. The highest score achievable was 100. Half of the participant scored the full 100 points. The average score on the test was 92.31 out of 100 points ($SD = 9.60$), the lowest score was 75 out of 100 points.

4.3.2 Take-over decisions

A total of 556 decisions were recorded. These decisions include both the decisions that a take-over was necessary and the decision that no take-over was necessary. There were large individual differences in the number of times a participant decided on a take-over. While one participant only thought a take-over was necessary in one situation, another decided on a take-over in 75% of the scenarios ($M = 30.62$, $SD = 17.52$). There were also large individual differences in the take-over scores (the percentage of scenarios in which a participant decided correctly) with a lowest score of 42.11% and a highest score of 90.48% ($M = 70.98$, $SD = 11.25$). Group 2, which received system information, appeared to have a slightly better performance with a mean take-over score of 73.29% ($SD = 9.53$) compared to group 1 which had a mean take-over score of 68.67% ($SD = 12.68$). GEE models were created to further investigate the effects of information group on the correctness of the participants actions. In the GEE analysis, a suitable correlation matrix method needs to be selected to indicate the general data structure to create a model (Ziegler & Vens, 2010). All working correlation matrix methods were explored, and showed that the method was very robust against changes of correlation between differences in Goodness of Fit (QIC) were marginal between models. The exchangeable method was used for the final results as the models from this method resulted in the lowest QIC of 672.43 (Cui, 2009; IBM Knowledge Center, n.d.; Sainani, n.d.). The GEE modelling showed no significant effects of system information on take-over score ($\chi^2(1, N = 556) = 1.190, p = .275$).

The scenarios were randomized for each participant to be able to judge the scenarios individually. Still, when the participants did not push the button to indicate a take-over, they would see how the car copes with the situation. As this may have resulted in a learning effect, the take-over decisions were also analysed over time. First, a graph was created to investigate take-over decisions over time. Upon visual inspection, an increase in appropriate decisions over time appears to be present (Figure 4.2). A GEE analysis confirmed a positive effect of time on the appropriate decisions made ($\chi^2(20, N = 556) = 119.907, p < .001$). It was investigated whether this effect was stronger for either of the information groups (Figure 4.3). Adding the information groups into the GEE analysis indeed showed an interaction effect of time and information group ($\chi^2(20, N = 556) = 52.991, p < .001$), while there was still no overall difference in take-over scores between the groups. The group without information (group 1) showed a stronger increase of appropriate decisions over time compared to the group with information (group 2).

Figure 4.2. Percentage of (in)appropriate take-over decisions over time.

Figure 4.3. Percentage of appropriate take-over decisions over time per group.

Some particular scenarios resulted in a relatively high number of inappropriate decisions compared to the others (Figure 4.4). In scenario 4 ‘Bike path’, 13 participants decided that a take-over was necessary even though this was not the case. In this scenario, the car needs to cross a bike path and give way to cyclists. In scenario 21 ‘Zone end’, only two of the participants decided on a take-over although it was necessary so as not to hinder other road users. In this scenario, the car leaves the residential zone and drives into a rural area as is indicated by a traffic sign. Outside the residential zone, cars are allowed to drive at 80 km/h. Figure 4.5 shows where the car leaves the residential area. In the system description, it is stated that “The traffic sign detection detects

standard round maximum speed signs with a red border”. As there was no standard speed sign but just the “end of residential zone” sign on the left side of the road, the car did not register this change and continued to drive at 50 km/h. When asked why they did or did not take over, 8 participants commented that they did not notice themselves that the maximum speed had changed even though this is a standard task in driving.

Figure 4.4. Percentage of participants that correctly decide to (a) rely on the car when possible and (b) take back control when necessary, per driving scenario.

Figure 4.5. Scenario in which the car leaves a residential zone and moves into a 80 km/h zone. The car does not detect any speed signs and thus continues to drive at 50 km/h. The driver needs to take back control.

4.3.3 Qualitative results

In this section, first the results of the discussion after each scenario will be presented. Then, a quick overview of the main observed statements and behaviours made by participants during the experiment will be discussed.

After each scenario, participants were asked why they decided to take back control or rely on the car. It became clear that it was difficult for participants to put into words what triggered them to decide to either take over or rely on the car. Although participants from the information group did sporadically answer in terms of functionalities as described in the system description, the most frequently given answers were the same for both groups. Acceleration/deceleration and steering behaviour by both the car and other road users as seen in the video footage were most frequently reported as the main reason why participants decided to take over or not. In particular the timing, and intensity of these driving behaviours in the videos were mentioned. Other reasons included deductions from other functionalities; for example, participants reasoned that if the car can detect lane markings it can probably detect pedestrian crossings.

During the experiment several reoccurring statements were found. Although participants in group 2 (the information group) scored high on the knowledge test, participants were surprised by the actions and abilities of the car in situations that had been literally described in the system description. In scenario 11, for example, the car drives along a road towards an intersection controlled by traffic lights. The car stops as the light goes from orange to red. It should have been clear that the car was able to detect and stop for the traffic lights as the system description stated that “The obstacle detection detects ... traffic lights, ... and intersections”. However, surprise was expressed, both verbally and physically, by multiple participants when the car stopped for the red traffic light.

Furthermore it was noted that participants that were clearly aware of a rule from the system description (as demonstrated by verbally stating it during the scenario) still expressed difficulty in making a take-over decision. For example, in scenario 18, the car approaches an obstacle lower than 30 cm and thus does not detect it and drives over the obstacle. Four participants mentioned during this scenario that they knew that the car did not detect obstacles of less than 30 cm. Three of them expressed confusion as they did not know whether the object was higher or lower than 30 cm, while one stated that it was very obvious how to proceed as the object was clearly less than 30 cm. Knowing the limitations of the vehicle may not be enough if critical information about a situation is not available or the consequences of one's decisions are unclear. In this case, participants may not know whether it is 'ok' to drive over a small obstacle.

Although behavioural observations were not part of the predefined measurements of this study,

they may still provide valuable insights regarding take-over decisions. It appeared that take-overs by participants in a situation that was both time and safety critical were all made too late. By ‘too late’ we mean that the timing of the take-over would have either: (1) created a dangerous situation for the driver and/or other road users; (2) or required other road users act to avoid an accident. In scenario 15, where a pedestrian starts trying to cross the street on a pedestrian crossing and steps onto the road. The car cannot detect pedestrian crossings, does not know to give priority and thus continues driving (Figure 4.6). All 19 participants (67.9%) that actually took back control were too late to intervene. All interventions took place while the car was already on or had even passed the pedestrian crossing.

Figure 4.6. Pedestrian crossing scenario. A pedestrian wants to cross. However, the car does not detect any other road markings besides the lines that indicate the course of the road. The driver is required to take back control as the car would otherwise continue to drive and the pedestrian had to step back to avoid being hurt.

4.4 Discussion and conclusion

This study investigated the effects of providing drivers with system information on their ability to decide whether to take back control in a partially automated car. The system information consisted of recurrent elements in current owner's manuals as this is the main way new car owners currently receive information about the automated systems in their car (Eichelberger & McCartt, 2016; Jenness et al., 2007). The information was mainly structural (Grotzer, 2002) as it will become infeasible to incorporate procedural rules for all possible situations in highly complex automated car systems. It was assessed whether this system information, can update a driver's mental model to the actual system capabilities, and support the driver in deciding whether to take back control. This was done by measuring the number of appropriate take-over and reliance decisions in a video based driving simulator experiment. The results of this study may support the decision making processes of governments and regulatory transport institutes about the need for theoretical (manual style) training and testing of drivers who start the use of partially automated vehicles.

The results of this study show no support for an overall effect of system information on appropriate take-over decisions. It appears that, overall, drivers are neither better nor worse at correctly deciding to rely on the car or taking back control when they have been presented with system information beforehand. Surprisingly, even information from the system description that was directly replicated in driving scenarios was not straightforward for drivers to act on in practice. Similarly, sometimes drivers were surprised about car behaviour that had been explicitly mentioned in the system description. Additional to these results, in critical situations that required a take-over, drivers did not respond in good time. In-car distraction is unlikely to be a cause as drivers were required to monitor the road continuously, and there were no secondary tasks. It remained difficult for drivers to accurately judge the capabilities of the car and decide how to act correctly. The main reasons participants gave for their take-over decisions were the visual cues of timing and intensity of acceleration/decelerations and steering made by the partially automated car and other road users. However, for the same situation, some considered braking as too late and too harsh while others found the deceleration to be very early and slow. It appears that again, participants were not certain on the cars functioning and capabilities (such as which action it would take next).

Overall, it appears that the system information did not create a more accurate mental model of the car's capabilities, and therefore did not change the take-over decision making accuracy. Structural system information in this form might not be a successful strategy to support drivers in understanding and interacting with a partially automated car during actual driving. The advantage of structural information is that it is conceptual and can encompass many situations that drivers might encounter (Eiriksdottir and Catrambone, 2011, Grotzer, 2002). However, it requires a lot of reasoning skills and remembering of the driver. Most participants in this study are highly educated, and likely to be acquainted with theoretical learning. It is expected that if this group cannot or does not apply the information, it will be even more difficult for people who are not accustomed to theoretical learning. Accessing, transforming and applying structural information in quickly changing driving tasks, while being in a new role of automation supervisor rather than manual driver, may be too demanding (Banks et al., 2014; Martens & van den Beukel, 2013). Presenting drivers with rule-based information however does not seem feasible due to the large number of complex rules that would need to be taught to encompass all the complex driving scenarios.

Different driver training strategies may need to be applied to support the driver in their take-over decisions. Although the scenarios in this study were randomized, there was still an observed learning effect. Experiencing the system through practice appeared to be an important part in learning when to take back control and when to rely on the system. Researchers in the automation domain such as Muir (1987) have supported the notion of physical practice with automated

systems to gain an accurate conceptual model. Although additional cost and time investments are required, relatively short training periods of a few weeks may be sufficient to reach stability in their learning curve (Beggiato, Pereira, et al., 2015; Weinberger, Winner, & Bubb, 2001). Combining practical and theoretical training may provide the right balance between ‘learning by doing’, and providing drivers with knowledge about important situations that occur sparsely. A recent study by Payre et al., (2017) shows that a combination of theoretical and practical training had a positive effect on both reaction time and self-reported trust. However, for both these approaches holds that providing training for the multitude of automated car systems that will be available may be impractical. In case of the emerging car-sharing concepts where drivers will regularly operate different cars, drivers would need to be trained for each system separately. Taking an in-car support approach may be more promising in supporting especially first-time drivers in partially automated cars. A real-time responsive interface and interaction with the car may overcome the limitations of theoretical and simulated training. The alignment of the driver’s expectations and the car’s capabilities may be achieved by providing the driver with necessary knowledge specific to that particular situation. It can continue to support drivers after the first driving period in a more moderate fashion to keep their conceptual models as accurate as possible (Beggiato, 2014; Beggiato & Krems, 2013). Furthermore, support can be extended and adapted as the driver becomes more experienced in working with the system.

4.4.1 Limitations

Some limitations about the system information materials need to be addressed. The core elements of the system description were chosen as a combination of recurring sections in owner’s manuals. Currently, user manuals provide text based information with some supporting schematics about: the distinct automated systems and their functionalities, the equipment and technical specifications (although not all user manuals include this section), and requirements for optimal performance including system limitations in certain conditions. Although this study strived not to deviate too much from current owner’s manuals, additional information was provided since we focussed on a vehicle with a set of capabilities beyond current commercially available vehicles. We therefore carefully designed our instruction to provide information about these elements to see if driver could apply this knowledge in dynamic scenarios. We realize that the technical details may appear to be overrepresented in the instruction materials while the conditions in which the system does or does not function may seem underrepresented, compared to current commercial owner’s manuals. However, the more advanced the systems will be, the more difficult it will be to describe all the situations under which the system does and does not work well. As the system had broader capabilities than the current commercial vehicles, the instructional materials may have been more complex as a result. The limited amount of listed conditions in which the car functions well may not have provided participants with enough reference for making the right take-over decisions,

even though we did not find that people used a strategy to rather be safe than sorry and take-over in all situations.

While the instruction materials were designed carefully to avoid ambiguity, some particular statements in the functionalities section may not have been completely clear for the participants. For example, as stated in the qualitative results, some participants were surprised that the car braked for a traffic light. This may have been due to the fact that the instruction manual states that the car can detect traffic lights, but does not explicitly state that it will brake accordingly. This may have led to participants taking back control more often than required.

The fact that this was a video based experiment poses an additional limitation. As there is no physical risk for the participants, the sense of urgency to take over is expected to be lower than in a real car. This can further explain the late reactions in situations that required a take-over. Getting an accurate feeling of speed and distance may also be more difficult in video based driving scenarios, which poses some limitations on the exact response times that participants showed or the actual moment of take-over.

The measures used in this study to assess the participants mental models may not be exhaustive. The knowledge test consisted solely of multiple choice questions and was only administered to group 2. It may be that group 1 would have scored similarly without receiving any system information. This possibility would need to be excluded in further studies by exploring the mental model all participants have of a system prior to the experiment. Important other aspects that form a mental model need to be included such as prior experiences. Also, participants found it difficult to verbalize why they decided to take over or rely on the car. This method should therefore be supported by including other measures.

Although randomization of the scenarios was implemented to avoid a learning effect, we still saw a learning effect in both groups. This is most likely due to the situations in which the participants did not take over. In these cases the video would play until the end and the participants could see how the car dealt with the situation. The group that did not receive information beforehand showed a stronger learning effect during the study. This may be as they needed to rely more strongly on the experience during the study to make their decisions. By presenting scenarios, the participants made their own inferences and judgements about the car's behaviour. Still, by analysing the take-over decisions over time, this study presents a thorough view of the effect of system information on take-over decisions. As an effect of time, but not of system information was found, experience/training appeared to play an important role in creating an accurate mental model of the system. Finally, although our set-up has allowed for repeated measurements and consequently provided more data points per participant, it is still possible that no differences were found between groups due to the smaller sample size of this study.

4.4.2 Conclusions

The aim of this study was to investigate whether system information would align drivers' mental models to the actual capabilities of a partially automated car, and support the driver in deciding whether they need to take back control. This system information was based on the current source of automated car system information for drivers: owner's manuals, but was adjusted to be tuned to systems that have much wider capabilities than current commercially available vehicles. Combining both the qualitative and the quantitative results, it appears that the mental models of the drivers were not (more) accurate after reading the system information. Informing drivers via owner's manuals may not be enough to support drivers in their new role. Combining theoretical training with practice may still provide the most accurate and efficient learning method, for example at driving schools, however this is a very time-consuming and costly solution. Furthermore, model specific training would be difficult to realise. Therefore we recommend to further investigate in-car support of drivers in partially automated cars. Real-time in-car information provides the opportunity to continuously update the driver's expectations and beliefs about the car, while being tailored to various situations and users. This study provides valuable insights for the further development and research of driver training strategies and identifies a possible need for more thorough in-car information, possibly even tuned to the specific driver and the specific condition one is driving in. We need to stress that currently, drivers do not seem to be prepared for their new role in partially automated vehicles. Owner's manual information, do not appear to provide drivers with the necessary tools to be able to decide whether it is necessary to take control of the automation, and in-car HMI solutions need to be considered.

Chapter 5

Current state of HMI in partially automated cars

This chapter is based on:

Boelhouwer, A., Van Dijk, J., & Martens, M.H. (2019). Turmoil Behind the Automated Wheel An Embodied Perspective on Current HMI Developments in Partially Automated Vehicles. In H. Krömker (Eds.), *HCII 2019: HCI in Mobility, Transport, and Automotive Systems* (pp. 3-25). Orlando, FL: Springer, Cham. doi: 10.1007/978-3-030-22666-4_1

Chapter 5. Current state of HMI in partially automated cars

5.1 Introduction

Car HMI may have a large influence on drivers' understanding of the automation. Especially as many drivers do not actively receive any information about their car's automation from their car dealer, and owner's manuals provide insufficient support for drivers that search for information themselves (see Chapters 3 and 4). It is therefore necessary to explore both how current HMI in partially automated cars inform drivers about the automation, and consequently to identify design opportunities for improvement.

Until now, the development and research on driver support through in-car HMI has been mainly addressed from a traditional cognitive psychology perspective and human centred design. In this traditional perspective, cognition is considered to be “the mental action or process of acquiring knowledge and understanding through thought, experience, and the senses” (Oxford Living Dictionaries, n.d.). Although specific perspectives of course differ from each other, the mode transition from automation to manual control is commonly described as a set sequence of consecutive mental processes and resulting physical actions. This perspective allows for the development of generally applicable driving behaviour models. Consequently, many HMI take a linear and generally applicable interaction approach. For example, if the car cannot cope any longer a general take-over request should be issued.

However, as automated car systems become more and more complex, a more holistic perspective on the ways that drivers gain knowledge about, and interact with, these systems may be necessary in the design of HMI to stimulate appropriate automation use⁶. This study therefore investigates driver support in partially automated vehicles from a different perspective: embodied interaction (Anderson, 2003; Clark, 2008; Wachsmuth, Lenzen, & Knoblich, 2012). Rather than defining cognition as a set sequence of cognitive processes and resulting actions in a defined set of scenarios, one may consider cognition as the entire system of continuous and simultaneous interactions between mind, body and world. Embodied interaction proposes that all knowledge and sense-making of the world emerges from a continuous and simultaneous interaction with the world (van Dijk, van der Lugt, & Hummels, 2014). As Anderson (2003) stated “cognition is a highly embodied or situated activity [...] thinking beings ought be considered first and foremost as acting beings”. Furthermore, embodied cognition states that all abstract symbols (including words) only gain meaning through embodied experiences and physical aspects. In this embodied perspective, the emphasis of gaining knowledge is thus more focused on the physical acting of a person in a very specific situation. By discarding the idea that cognition only occurs in the mind,

new design opportunities may be discovered. More emphasis can be put on the combination of mind *and* body making sense of situations in ongoing interactions with the current environment. This study therefore reviews current HMI of partially automated cars in the light of embodied interaction and considers three important characteristics of embodied interaction: suppleness (Isbister & Höök, 2007), bodily experience (Clark, 2008) and situatedness (Anderson, 2003). The interpretation of these characteristics will be explained in detail in Section 5.2.2.

The review focusses on the HMI of partially automated cars during Take-Over Request (TOR) by the car, and during automated mode. A TOR consists of feedback from the car that the driver needs to take back control from the automation. The general HMI during automated mode includes any Hands on Wheel Warnings (HOWW). These warnings indicate that the drivers have to put their hands on the wheel (or ideally eyes on the road). Since this is not a formal request to take over and is not linked to system limitations, this will be described as feedback during automation. Finally, while most review papers only discuss academic papers and patents, this review includes currently commercially available systems and systems that are being studied in experiments but are not yet on the market.

The goal of this review is to identify the current state of HMI during both the TOR phase and the automation phase in both literature- and commercially available systems. We will examine how HMI designs currently consider the main characteristics of embodied interaction, and which unexplored design spaces may be used as opportunities for the design of HMI systems of partially automated cars. Concluding, this study investigates two main research questions: (1) What embodied interaction aspects are currently used in car HMI of partially automated cars? (2) Which embodied interaction aspects are currently unexplored in HMI of partially automated cars and may be used as inspiration in new HMI designs.

5.2 Methods

5.2.1 Data collection

The materials gathered for this literature review consisted of the following types: journal papers, conference papers, work-in-progress papers, technical reports and product documentation of commercial cars. It was decided to include technical reports and product documentation of commercial cars as the current development of HMI in automated car systems is proceeding fast. Including these material types allowed the study to review the latest developments in both industry and academia. Both the commercial car systems as the concepts in literature were reviewed on 1) the HMI during TORs, and 2) the HMI during automated mode. As the majority of the gathered materials does not specify the level of automation nor the exact Operational Design

Domain (ODD), it was decided that the requirement for inclusion was that the system automated both lateral and longitudinal control simultaneously.

The literature papers and reports had to be written in English, and published after 2008. Although other studies have conducted reviews on shorter periods, we believe that it is necessary to include sources of a 10 year period. Condensing this work into a short snapshot would undermine the continuous progress within the field. Literature reviews and meta-analysis studies were excluded. The following leading research databases were used to collect the journal- and conference papers: Web of Science, IEEE, Scopus, Google Scholar.

For the TOR reviews, we solely considered systems that indicate a take-over request due to system limitations. Therefore Hands on Wheel Warnings (HOWWs), which prompt the driver to keep their hands on the wheel without the need to disengage automation, were not reviewed among the TORs. However, the HOWWs were included in the review of the general HMI during automation. These warnings are often included in car systems both for legal reasons and with the intention to keep the driver ready to take back control instantly.

Literature concepts – TOR. For the TOR review on literature concepts, the literature papers had to be specifically focusing on the design or testing of HMI support during TOR. Studies that only used HMI as a means to perform their experiment on a different topic were excluded. The following keywords were used in the research databases: ((“Autonomous” OR “Self-driving” OR “Automated”) AND (“HMI” OR “Human machine interaction”) AND (“Design” OR “Feedback”) AND (“Take-over” OR “Take over” OR “Transition” OR “Warning” OR “Request”) AND (“Car”)).

Literature concepts – HMI during automation. For the review on general HMI feedback during automated mode, only studies that specifically address the development and testing of an HMI design were included. Studies that use an HMI purely as a means to perform their experiment on a different topic were excluded. The search entry for materials on HMI systems during automated mode contained the following keywords. ((“Autonomous” OR “Self-driving” OR “Automated”) AND (“HMI” OR “Human machine interaction”) AND (“Interface” OR “Feedback”) AND (“Car”)).

Commercial cars – TOR and HMI during automation. The selection of commercial car brands was done based on their official user manuals and websites. The car system had to be available for purchase at the time of this review. To avoid an incomplete review, only systems that included all necessary information for the categorization were considered. Of the current available systems, only two formally include a TORs (Audi MediaCenter, 2017; Cadillac, 2018). Therefore the TOR review included just these two commercial car systems. (As mentioned before, the systems do

include HOWWs. These are reviewed in the ‘general HMI during automation’ section.)

5.2.2 Data coding

The materials gathered were labelled on three main use qualities of embodied interaction: suppleness (Isbister & Höök, 2007, 2009; Sundström & Höök, 2010), bodily experience (Clark, 2008; van Dijk et al., 2014) and situatedness (Anderson, 2003). Although not exhaustive, these are discussed frequently within the embodied interaction domain and are generally excepted to portrait (some of) the core elements. Each quality will be discussed briefly with their respective measures. Some of the specific variables were used from the study by (Mirnig et al., 2017) who created a categorization framework for control transition interfaces. Table 5.1 and Table 5.2 show all variables that were examined, respectively for the TORs and general HMI during automation.

Suppleness. Isbister, Sundström and Höök, (2009, 2010) introduced the use quality of suppleness. They stressed designing for supple back and forth interaction between a user and system, which can be seen as a fluent ‘dance’ (Sundström & Höök, 2010). The Webster dictionary definition of supple is considered the base for this use quality: “easy and fluent without stiffness or awkwardness”. In this study, we categorized the TORs on three supple qualities. The first was whether the transfer is introduced abrupt or gradually: Temporal Output Mode (Mirnig et al., 2017). The TORs could be categorized as being shown once, several times, or incremental. It was specified whether the support was given: before/during deactivation of the system, or before a hazard. It was important to take this into account as the time to take-over would be either the time before a collision or deactivation of the system. The second variable was the amount of time the driver has to take back control: Time to take over. More specifically, how much time does the driver have after the TOR until the system disengages or the car crashes? The third item entailed the use of Social cues. The research and design area of embodied interaction is increasingly focusing on incorporation of natural social interactions in artificial intelligent systems (Dourish, 2004). As we are social beings, we engage in continuous social interactions to understand and act on the world (De Jaegher & Di Paolo, 2007). Therefore we investigated whether there is any use of social cues that we use daily in human to human communication in the HMI systems. These could for example facial expressions and gestures.

Bodily experience. Inclusion of the body in making sense of the situation is at the core of embodied interaction (Clark, 2008; van Dijk et al., 2014). Our entire body and all our senses are included in learning, and creating an understanding of the world. By including multiple senses in a feedback system, overload may be reduced or prevented. Therefore, the way the driver has to disengage automation (Input) was included in this review as well as the modality of the TOR itself (Output). For the input, we used a similar classification as Mirnig et al. (2017) which

included physical, touchscreen, gesture and speech. However, touchscreen was made into a sub classification of physical and we additionally included the options for activity recognition and ‘other’ input. Activity recognition includes all forms of system initiated recognition such as eye movement recognition or posture recognition. The physical class contains input through buttons, the steering wheel, the pedals and touchscreen. For the output modalities, we included all five basic modalities: visual, auditory, haptic, smell, taste. As directional forces such as acceleration and deceleration are a large part of the driving experience, the vestibular sense is also included.

Situatedness. As the name would make one suspect, the situatedness describes how the meaning of interactions with technology cannot be seen in isolation from the context in which it occurs: interaction is always situated (Anderson, 2003). Cognition relies on embodied interactions that take place within a specific situation. For example, a symbol or gesture can have a very different meaning in different contexts and for different people. In this study, TORs were investigated on whether or not they are Adaptive to the driver and driving situation. Is the feedback the same for all drivers and all their driver states? Also, is the feedback the same in all driving situations?

Table 5.1.

Data coding scheme for TOR feedback.

TOR						
Suppleness			Bodily experience		Situatedness	
Temporal output mode	Time to take over	Social cues	Output of TOR	Input to disengage automation	Adaptive to driver	Adaptive to driving situation
(O)nce, before deactivation	Seconds before deactivation	(Y)es	(V) Visual	(P) Physical	(Y)es	(Y)es
		(N)o	(A) Auditory	(S) Speech	(N)o	(N)o
(O)nce, during deactivation			(C) taCtile	(G) Gesture		
(O)nce, before hazard			(S) Smell	(A) Activity recognition		
			(T) Taste			
(S)everal				(O) Other		
(I)ncremental			(E) vEstibular			

Table 5.2.

Data coding scheme for HMI during automation.

HMI during automation			
Suppleness	Bodily experience	Situatedness	
Social cues	Output of HMI system	Adaptive to driver	Adaptive to driving situation
(Y)es, ..	(V) Visual	(Y)es, ..	(Y)es, ..
	(A) Auditory		
(N)o	(H) Haptic	(N)o	(N)o
	(S) Smell		
	(T) Taste		
	(E) vEstibular		

5.3 Results

5.3.1 Reviewed materials

An overview of the results can be found in tables C.1 until C.6 in Appendix C. Seven different commercial car brands were selected for this review. All systems have the option to simultaneously activate the automation of lateral and longitudinal control. As the systems have different names across brands (and sometimes even within the brand) they will be addressed by their company assigned name on their official websites and or user manuals. The included brands and systems are: 1) Audi – AI Traffic Jam Pilot (Audi, 2018; Audi MediaCenter, 2017), 2) Tesla – Autopilot (Tesla, 2018), 3) Cadillac - Super Cruise (Cadillac, 2018), 4) BMW – Steering and Lane Guidance Assistant (BMW, 2015), 5) Volvo – Pilot Assist, 6) Mercedes – Drive Pilot (Mercedes-Benz, 2016, 2017). All commercial systems will be reviewed on their general HMI during automation (including HOWW). However only two of these systems included a formal TOR since they allow the driver to be temporarily out of the loop due to a traffic jam assist. Therefore only these two system could be reviewed on its TOR (Audi MediaCenter, 2017; Cadillac, 2018).

A total of 20 literature papers were reviewed on their TOR concepts in this analysis. Some papers discussed multiple concepts within the same paper. These were considered as individual concepts, resulting in a total of 31 concepts that were reviewed. 15 papers were selected for the general HMI during automation. Again, as some papers presented multiple concepts, a final total of 17 concepts were reviewed. None of the literature concepts contained HOWWs, therefore these could not be included in the general HMI review.

5.3.2 Take-Over Request (TOR)

Commercial cars. Formally, only the two of Audi and Cadillac issue a TOR (Audi MediaCenter, 2017; Cadillac, 2018). Therefore only these two commercial systems will be reviewed here. The remaining systems all require the driver to continuously keep their hands or eyes on the road. Regarding suppleness, Audi AI traffic jam pilot provides multiple TORs before the system disengages due to system limitations. Cadillac Super Cruise provides one TOR before deactivation. During the second warning, at the end of the take-over period, the system already deactivates. Both systems provide a social cue in the form of a symbol in which hands are holding a steering wheel (or an animation that the hand grab the steering wheel).

Considering bodily experience, the TORs are in both cases visually displayed on a screen. Cadillac Super Cruise uses additional use of colour and illumination in the steering wheel. The visual cues are complemented in both systems with auditory beep(s) and/or a spoken take-over message. Cadillac Super Cruise includes vibrations in the seat as a TOR. Audi includes a short brake jerk and tightens the safety belt three times during the second warning. Drivers can disengage the automation in both systems by turning the steering wheel, pressing one of the pedals or pushing a button.

Regarding situatedness, the reviewed systems are not adapted to the driver. This means that the same message is given regardless of the current driver (state) or activity he is currently performing. None are adapted to the driving situation. The feedback does not change according to, for example, the reason that the car needs to transfers back control.

Concluding, we found that the two reviewed commercial car TORs are very similar on the reviewed embodiment aspects. The Audi system is slightly more supple as it provides multiple TORs before the system disengages. Both TOR systems provide visual and auditory cues. These are complemented with vibrations (Cadillac), seatbelt tightening or vestibular feedback through braking (Audi). The situatedness of the TOR feedback is lacking as they did not change their form to the driver, nor to the specific driving situation.

Literature concepts. Considering suppleness, the majority of the concepts ($N = 20$) consist of a single TOR before a detected hazard (without the automation deactivating). Two concepts are similar to the commercial car systems as they provide one take-over request during which the system is immediately deactivated (Naujoks, Mai, & Neukum, 2014; van der Heiden, Iqbal, & Janssen, 2017). Eight of the reviewed concepts give several warnings before deactivation. Five of these warnings increase in intensity and cue modalities over time. The time that drivers have to take back control before deactivation or impact ranges widely from 10 seconds to ‘a few minutes’. Two studies only report that the drivers had ‘sufficient’ time to take back control

(Naujoks, Forster, Wiedemann, & Neukum, 2017; Zimmerman & Bengler, 2013). It is not stated how much this specifically is. As a social cue, a few of the concepts ($N=5$) include a symbol with hands on the steering as is also seen in the commercial car systems (Figure 5.1). One concept uses a distressed voice in a verbal message in order to portrair urgency (Politis, Brewster, & Pollick, 2017).

Regarding bodily experience, 23 of the TOR concepts give auditory feedback. This feedback is divided into abstract beeps ($N=16$), and verbal messages ($N=2$), while the rest of the concepts combines both ($N=5$). The majority of the concepts ($N=17$) use a display. These include standardized symbols, text and use of colour or flashers. The colour red is used in all cases to indicate an immediate required take-over. Of the display messages, thirteen are complimented with auditory or haptic feedback. Four of the concepts include lighting. While two concepts have a simple LED on the dashboard, the concept by (Borojeni, Chuang, Heuten, & Boll, 2016) has a LED strip on the steering wheel that can light in directional patterns. This way, it hints towards the required steering direction after take-over. Two studies included mechanical transformations in their concepts. In the concept by Borojeni, Wallbaum, Heuten, and Boll (2017), part of the steering wheel was replaced with grips that change direction during the TOR depending on the required steering direction. In the concept by Kerschbaum, Lorenz, and Bengler (2015), the upper part of the steering wheel moves backwards during automation and is shifted back during the TOR. This is mainly done to emphasize the need to take back control. Eight of the concepts include vibration feedback. This is mainly applied in either the driver seat or steering wheel. However, the concept in Politis et al., (2017) gives vibration feedback in a wristband. The vibration feedback in the driver seat is either static or dynamic. In case of dynamic feedback, the vibration shifts along rows, creating the ‘illusion’ of motion or direction. Besides three papers, drivers can take back control in all concepts by engaging with the steering wheel or pedals.

Figure 5.1. Examples of TORs that include a ‘hands on wheel’ symbol in literature. Left by Naujoks et al., (2017) and right by Melcher, Rauh, Diederichs, Widlroither, and Bauer (2015).

Considering situatedness, one of the literature TORs is adaptive to the driver. The concept by (Naujoks et al., 2014) shows the TOR on the driver's mobile device if he is using this. More than half of the concepts ($N = 16$) adapt to the driving situation. Most of these concepts contain a suggested (steering) action based on the situation. The way in which this is done ranges widely. Some provide a suggested steering direction through vibration or lighting direction while others adapt the colour or symbol accordingly. The concept by Borojeni et al. (2017) even adapts the shape of the steering wheel according to the suggested steering direction. Some concepts do suggest a direct action but rather provide boundaries in which the driver can operate. For example, the concept by Zimmermann and Bengler (2013) shows the intent and expected actions of other road users, while the concept by Lorenz, Kerschbaum, and Schumann (2014) shows an overlay on the driving lane whether it is safe to continue driving there. Two concepts show the upcoming situation visually and why the driver needs to take-over, for example dense fog or roadworks.

Concluding, the majority of the literature concepts present one or multiple TORs before deactivation of the automation. This is expected as it is easier to implement warnings before deactivation of automation as a pre-set in an experimental setting, compared to in a car driving on the road. The variety of social cues is scarce. More variety is found in the bodily experience but only in the output. The variety consists of physical shape changes, verbal messages, dynamic vibrations and lighting. However, the main outputs are still displays and auditory beeps. Only one of the concepts adapts to the driver. However, more concepts adapt to the specific driving situation. In these cases they mainly provide a suggested action, boundaries after the transfer of control, or reasons for the TOR.

5.3.3 HMI during automation

The result tables are situated in appendix C. Table C.3 shows the results for general HMI during automation in commercial cars. Table C.4 shows the results for general HMI during automation in literature concepts.

Commercial cars. Considering suppleness, most of the commercial systems ($N = 5$) include a Hands on Wheel Warning. While it is not indicated exactly how long these warnings continue before the system disengages or stops the car, all systems provide these warnings several time while increasing the intensity (in any form). All systems use a 'hands on wheel' symbol as a social cue to indicate that the driver needs to keep their hands on the wheel.

Regarding bodily experience, all systems use a visual display on a screen with illustrations, symbols, text and changing colours to provide feedback. If drivers keep their hands or eyes too long off the road they will receive auditory beeps as a warning and vibrations in the steering wheel or seat. Cadillac Super Cruise includes illumination and changing colours in the steering wheel as

additional feedback on the automation state. Drivers get visual feedback of the current car actions as they see the turning of the steering wheel. Besides the visual feedback, drivers can feel the car's actions through the turning of the wheel.

With regard to situatedness, all HMI systems during automation are partially adapted to the driver as they sense whether the driver has their hands on the wheel, or their eyes on the road, and prompts a HOWW accordingly. There is some variation to the extent in which the systems are adapted to the driving situation. However, all of them show a combination of automation mode, detected vehicles, lane markings and speed limit.

Concluding, the general HMI during automation of commercial cars is very much the same across the systems on the investigated aspects. The suppleness with regard to social cues is limited to 'Hands on the wheel' symbols. The output is mainly given through displays, auditory beeps and vibrations in the steering wheel. The feedback is partially adaptive to the driver as it issues a 'hands on wheel' (or eyes on road) message in case the car detects that the hands are not on the wheel (or the eyes are not on the road). The feedback is adaptive to the driving scenario as all systems present the detected vehicles, obstacles, speed limit and/or lane markings. Figure 5.2 shows examples of HMI during automation in the Audi (A8) and Tesla systems.

Figure 5.2. Examples of HMI during automation. The left dashboard is by Audi for their A8 (CHNL, 2017), the right dashboard is by Tesla (Tesla, 2015).

Literature concepts. With regard to suppleness, two concepts use the social cue of showing 'hands on a steering wheel' (Naujoks et al., 2017; van den Beukel, Van Der Voort, & Eger, 2016). While the concept by Naujoks et al. (2017) uses this to indicate manual driving mode, that by van den Beukel et al. (2016) uses it as a soft warning in case of potential hazards. Two concepts use facial expressions in emoticons as social cues to indicate the confidence of the automated system (Beller, Heesen, & Vollrath, 2013; Rezvani et al., 2016). Karatas et al., (2017) use human's tendency to engage in joint attention/gaze to redirect the driver's attention. Their concept contains three physical mini robots on the dashboard that turn their head from and towards the road ahead. Finally, the concept by Hester, Lee, and Dyre (2017) uses small talk to engage with the driver, which consisted of sentences that were either driving related or not.

Considering bodily experience, six of the concepts provide multimodal feedback. These are combinations of auditory, visual and/or haptic stimuli. Eleven of the concepts include visual feedback, most of which are on displays ($N = 9$). Two concepts use lighting in their feedback (Karatas et al., 2017; van den Beukel et al., 2016). In Karatas et al. (2017) this is used to intensify the movement of the physical dashboard robots (as described above). Van den Beukel et al. (2016) uses light in the windscreen as a soft warning to direct the driver's attention towards potential hazards in the driving environment. The concept by Karatas et al. (2017) is the only one to use movement of mechanical objects in their HMI. Two concepts use tactile stimuli. Telpaz, Rhindress, Zelman, and Tsimhoni (2015) use vibrations in different parts of the driver seat to indicate approaching vehicles. The concept by Wi, Sodemann, and Chicci (2017) consists of a high resolution haptic surface the driver can touch with his fingers. The authors report that the concept may be used for visually impaired passengers of automated cars, but an exact function of the device is not specified. The use of auditory feedback is split evenly between beeps and verbal statements. The study by Nees, Helbein, Porter and College (2014) uses auditory icon sounds. They describe these sounds as “non-speech sounds that bear some ecological relationship to their referent processes”. An example is a water gurgle sound to represent the message that fuel is running low.

With regard to situatedness, four of the reviewed concepts are adaptive to the driver in some form. The concept by Karatas et al. (2017) tries to engage the driver in looking at the road by personification (small robot looking at the driver and then looking at the road) when the driver is inattentive. Similarly, the concept by Telpaz et al. (2015) only starts the vibration feedback if the driver is not looking at the road, to provide information about the surrounding traffic. The concept by Gowda, Kohler, and Ju (2014) shows adaptive information on the driver's condition during automation. What this information exactly entails is not specified. While the study by Wi et al. (2017) is directed specifically at visually impaired drivers, the feedback is not dynamically adapted to the driver during automation. Almost all concepts are adapted to some degree to the driving situation ($N = 13$). They use a variety of combined methods to show adaptive feedback about the driving situation. Five of the concepts show the currently detected elements of the driving situation through a display, such as road users, lane markings and traffic signs. All of these five concepts also include the planned next action of the car, such as an upcoming turn or brake. The concepts by Telpaz et al., (2015) and van den Beukel et al., (2016) change the location of their feedback, which are respectively vibration and illumination, according to the detected hazards. While Hester et al. (2017) uses casual remarks and questions about the driving situation to engage the driver, Hock, Kraus, Walch, Lang, and Baumann (2016) adapt the verbal level of information according to the situation. For example, in some situations the system only mentions the current action “the car is braking”, while in other situations it gives the reason why it is performing this action “the car is braking because a traffic jam is coming up ahead”. Lorenz et al.

(2014) uses a direct overlay on the windscreen to show whether it is safe to continue in that lane after deactivation of the automation. Three of the concepts display the confidence of the system to continue in automated mode (Beller et al., 2013; Helldin, Falkman, Riveiro, & Davidsson, 2013; Rezvani et al., 2016).

Concluding, the general HMI during automation in literature concepts shows a variety of supplied social cues. These cues mainly include facial expressions, shared gaze, a 'hands on wheel' symbol and small talk. The bodily experience of literature HMI concepts shows some variation. Only a small part of the literature concepts is adaptive to the driver. The ones that are, mainly show the driver condition or provide feedback if the driver is not paying attention. The feedback is adaptive to the driving situation in most concepts. In these concepts the feedback shows the confidence of the automated system, the detected environment and detected hazards. Some concepts change the location of their feedback according to the environment and next actions of the car.

5.4 Discussion and conclusion

The goal of this study was firstly to identify the current state of embodied design elements in driver support in partially automated cars. This way, new design spaces may be discovered to guide the design of innovative driver support in automated vehicles. To achieve this, partially automated car systems from literature and industry were reviewed from an embodied perspective. More specifically, we reviewed TOR feedback and the general HMI during automation on suppleness, bodily experience and situatedness.

5.4.1 Design opportunities TOR feedback

Several opportunities for new designs were found in the current TOR feedback systems. Firstly, most commercial car systems do not provide a formal TOR since the driver is considered to continuously monitor the road. Rather the system disengages when it can no longer function with only a simple visual or auditory cue. While we recognize that this is most likely a technical limitation, implementing multiple incremental TORs before system disengagement may greatly improve the suppleness (Gold, Damböck, Lorenz, et al., 2013). Especially as it can be very difficult for drivers to recognize themselves when the system reaches its limits, the system should indicate its limits as clearly as possible (Boelhouwer, van den Beukel, Van Der Voort, & Martens, 2019b; Carsten & Martens, 2018). Second, the use and variety of social cues was very limited in both commercial cars and literature concepts. Social cues may create more easily understood, fluent and accepted car-driver interactions. These may for example include social behaviour such as facial expressions, or gestures such as pointing or turning towards a joint interest (Cassell, Bickmore, Vilhjálmsón, & Yan, 2000). Third, while literature showed an increasing variety of

TOR output methods, TORs of commercial cars mainly kept to displays, beeps and steering wheel vibrations. It is important to transfer this development into commercial cars as dividing feedback to different senses may prevent overloading of the driver during take-over. Alternative output modes may be useful as drivers are engaged in non-driving tasks and not holding the steering wheel or looking at the dashboard. Lastly, both literature and commercial cars lacked situated feedback to the driver. This leaves a large opportunity to design driver adaptive feedback systems. The request may for example take the current activity of the driver into consideration. This is especially relevant in higher level automated cars where the driver may be immersed in different activities such as work. In order to create a safe mode transition the system should take the driver into consideration and adapt the feedback accordingly. This can be done not only by timing, but also by changing the location, intensity or modality of the information according to the driver's activity.

5.4.2 Design opportunities general HMI during automation

Design opportunities for general HMI during automation were also identified. First, although a few concepts with social cues were presented in literature, only 'hands on wheel' symbols were present in the commercial cars. Again, there is an opportunity to transfer more variety of social cues to commercial cars. The literature concepts already included facial expressions, small talk and mutual gaze. It is encouraged to expand the development of these and new cues to aid the driver in understanding the car through continuous fluent interactions (Damböck, Kienle, Bengler, & Bubb, 2011; Flemisch et al., 2003). Second, the bodily experience in general HMI during automation mainly consists of visuals, audio and vibrations. This holds for both the commercial cars and literature concepts. An opportunity is found to include other senses that may be less obvious at a first sight such as smell (Dmitrenko, Maggioni, Thanh Vi, & Obrist, 2017; Kaye, 2004), taste and the vestibular sense (Chance, Gaunet, Beall, & Loomis, 1998; Peterson, Wells, Furness, & Hunt, 1998). Although a few concepts use braking as vestibular feedback, it can be explored further as the lateral and longitudinal forces make up such a large part of the driving experience, and seems to be a natural cue for passengers of vehicles to respond so. Developing other forms of vestibular feedback may improve the situational awareness of drivers in automated mode while they perform non-driving activities (Peterson et al., 1998). Third, with regard to the situatedness, the HMI in commercial cars and literature are mainly adapting the timing of their message to the driver state. The form or message content however does not change. As previously stated, it may be necessary to design driver dependent feedback due to the different activities the driver may be engaged in during automation.

5.4.3 Limitations

Some limitations of this review have to be taken into account. We recognize that we may have missed papers or car systems that would have been relevant to this review. The search terms described in the method section were carefully chosen, however they may still not include all relevant papers. New commercial or industrial concepts may have been missed in particular as the development of automated cars is currently proceeding so fast. Another limitation is that, as mentioned before, the three reviewed embodied characteristics (suppleness, bodily experience, situatedness) do not represent every aspect of embodied interaction. No method to review interactional systems on their embodiment exists. However, we chose to take these key elements of embodied interaction as a guideline to explore HMI in partially automated car systems, as they represent the main concepts.

5.4.4 Conclusions

We firmly believe that embodied interaction holds a great promise for all next generation automated vehicles. While often the industry aims to fight human factors issues by improving vehicle technology, we believe that this may even enlarge some classic human factors issues. Therefore, the role of self-explaining and supportive feedback will even become more important as technology becomes more and more complex. Embodied interaction holds a great promise for both the TOR feedback and general HMI during automated. For TOR feedback, new embodied designs are encouraged to focus especially on the development of social cues, in- and output methods and adaptivity to the driver. For the general HMI during automation, new embodied design opportunities are in the output methods and adaptivity to the driver. By including these embodied elements, we can create HMI designs that foster a more fluent and natural interaction movement between automation and manual driving, reducing the need to invest in extensive training. This entails keeping drivers in the loop during automation so they are not overwhelmed at transfer of control, and support fluent transfer back to manual driving. Including the identified lacking characteristics of embodied interaction such as varying output modes and adaptivity to the driver and driving situation in future HMI may create safer, more efficient and effective car-driver interactions in automated cars.

Part III

Exploration and validation of a Digital In-car Tutor

Chapter 6

Inspiration from driving instructors' feedback strategies

This chapter is based on:

Boelhouwer, A., Van den Beukel, A.P., Casner, S. M., Van der Voort, M.C., & Martens, M.H. (2020 Manuscript submitted for publication.). Adaptive Feedback Patterns in Driving Instructors: Towards an Adaptive Digital In-Car Tutor for Drivers of Complex Partially Automated Cars.

The data of this study is freely available at:

OSF.IO/7JRKH

Chapter 6. Inspiration from driving instructors' feedback strategies

6.1 Introduction

Combining the results of our prior studies (Chapters 3, 4 and 5) a Digital In-car Tutor (DIT) is proposed as a time efficient and car model specific method to support drivers in learning about, and safely using, the automation in their car. Such a DIT gradually introduces the driver to the various automated function in the car *during regular drives*. The driver can then directly apply the information and is assisted in trying out the automated functions.

6.1.1 Support through a Digital In-car Tutor

We specifically propose a Digital In-car Tutor (DIT) that not only gives initial information about the automated systems in the car but also guides the drivers in trying out the functions during regular drives. Such a DIT appears promising for multiple reasons. First, drivers can receive both theoretical and practical training without having to invest additional time and money for training at an external facility. This is especially important as theoretical information alone does not appear to sufficiently support drivers in understanding and appropriately using car automation (Chapter 4). Combining theory with practical training however is suggested to be more effective (Beggiato et al., 2015; Ebnali, Hulme, Ebnali-heidari, & Mazloumi, 2019; Weinberger, Winner, & Bubb, 2001). Second, the training and learning feedback can be provided intensively, and over an extended period of time. This extended training can be beneficial for retaining an updated mental model (Beggiato & Krems, 2013; Kintsch, 1998; Payre et al., 2017), and safer automation use (RACV, 2016). Third, the tutor may be adaptive to the needs and performance of the driver, but also to the specific driving situation so the driver can directly apply the information (see also Chapter 5).

6.1.2 Adaptive and naturalistic driver support

Studies like that by Beggiato et al. (2015) have already proposed a useful set of HMI elements that should be presented at any time during automation. Still, in order to create an accurate mental model, the communication of a DIT may need to adapt to the three main elements of driving situations: 1) the (complexity of the) driving situation, 2) the driver and 3) the car state. First, as discussed in the previous chapter, making the DIT's information adaptive to the current driving situation (and corresponding car state) may be crucial to ensure a thorough understanding of the automation. Relating the information of the DIT directly to the current driving situation may make it easier for drivers to comprehend and apply it. Additionally, as it has been proposed that the overall complexity of the driving situation may have an impact on the drivers mental workload,

distraction and take-over performance (Gold, Körber, Lechner, & Bengler, 2016; Lyu, Xie, Wu, Fu, & Deng, 2017; Radlmayr, Gold, Lorenz, Farid, & Bengler, 2014), it may be necessary to adapt the form or content of information to the complexity of the driving situation to avoid overload. Second, the information may need to adapt to drivers as they greatly vary in the characteristics that will influence their interactions with the system. This is already widely done in classrooms (Bloom, 1984) and is applied more recently in robot tutors (Leyzberg, Spaulding, & Scassellati, 2014). Characteristics that need to be taken into account may include: prior experience with similar systems, confidence in using new technology, performance and learning capabilities (Clement, Roy, Oudeyer, & Lopes, 2015; Hoff & Bashir, 2015; Leyzberg et al., 2014; Ropelato, Zünd, Magnenat, Menozzi, & Sumner, 2017; Simon, 2005). Last, as Beggiato, et al., (2015) already established, the information can adapt to the car state to provide continuous information on the planned next actions and required actions by the driver.

Multiple studies have shown learning benefits of digital tutor that use forms of natural communication. Naturalistic communication such as gestures, body language, facial expressions but also word use and intonation all contribute in building a relationship between a student and tutor (Breazeal, Kidd, Thomaz, Hoffman, & Berlin, 2005; Kennedy, Baxter, & Belpaeme, 2015; Kennedy, Belpaeme, & Baxter, 2017). A positive relationship and emotional- and motivational feedback has shown to: increase the willingness to take advice, increase motivation, and reduce anxiety or frustration (Castellano et al., 2013; Kanda, Hirano, Eaton, & Ishiguro, 2004; Woolf, Arroyo, Cooper, Burleson, & Muldner, 2010). Natural communication by a tutor can also have an impact on the overall clarity and understandability of the interaction (Breazeal et al., 2005).

6.1.3 This study

The goal of this study is to gather inspiration for an adaptive and naturalistic DIT that helps drivers to understand, and safely use, partially automated cars in the first use period. More specifically, we investigate whether and how the communication of a DIT practically needs to be adaptive to the (complexity of) the driving environment and the driver. To achieve this we video recorded and analysed the tutor patterns of professional driving instructors during their lessons. This particular interaction was chosen as it shows a similar dynamic as one might see between a future DIT and a driver. In this metaphor, the DIT takes the place of the driving instructor and guides drivers in using the new car automation. While supervising automation is a very different task than manually driving (Martens & van den Beukel, 2013), the process of learning to which elements one needs to pay attention while supervising is similar to that in regular driving lessons. During driving lessons, instructors have to continuously provide higher-order instructions to teach driving students which driving situations they need to look out for, and how to act accordingly (Scott-Parker, 2017; Scott-Parker, Senserrick, Simons-Morton, & Jones,

2014). Observing driving instructors and their students would provide us with externally valid inspiration for a DIT. Both quantitative and qualitative analyses were conducted on the video recorded driving lessons to identify natural (non)verbal tutoring patterns, and their adaptation to the complexity of the driving environments and to the students.

Previous studies have extensively researched (non)verbal communication between driving instructors and their students (Goodwin, Foss, Margolis, & Harrell, 2014; Scott-Parker, 2017; Scott-Parker et al., 2014; Watson-Brown, Scott-Parker, & Senserrick, 2018). Still, it remains unclear how the communication of the instructor adapts to both the student and the driving situation. Consequently, two important questions remain unanswered regarding the development of an adaptive DIT. First, it is unclear if, and how, a DIT specifically needs to adapt its feedback to the complexity of driving situations. Second, how do drivers need to be supported through a DIT in the initial use period to create and maintain an accurate mental model of the automation? Overall, this study provides: an overview of natural tutoring patterns in driving instructors and practical recommendations on how these may be used for the design of an adaptive and naturalistic DIT to support drivers during their initial use of partially automated cars.

6.2 Methods

6.2.1 Participants

In this study we observed instructors and their students during car driving lessons in real life settings. It was specifically decided to observe driving instructors as they are trained and experienced in tutoring their students. In the Netherlands, only certified driving schools and driving instructors are allowed to provide driving lessons. Therefore, all instructors in this study were certified employees of the participating driving schools. Instructors needed to have at least one year of teaching experience. Students needed to have finished at least five prior lessons. This was a requirement to avoid additional pressure on often already nervous new driving students. 8 driving instructors and 18 students from 3 different driving schools participated in the study. The lessons of 2 students were omitted due to malfunctioning video equipment, resulting in a total of 16 student videos for analysis. The majority of the instructors was male ($N = 7$) with an average age of 51.6 years ($SD = 10.8$, range = 33-61). The instructors had an average of 18.9 years ($SD = 14.4$, range = 1-40) of work experience as a driving instructor. The average age of the participating driving students was 19.6 years ($SD = 2.7$, range = 17-26). The students had received an average of 27.1 lessons ($SD = 13.3$, range = 5-53) (45 minutes each) at the start of the experiment.

6.2.2 Materials and set-up

All driving instructors filled out a standard demographic questionnaire before the experiment about their age, gender, nationality, experience as an instructor, and interest in technology. Students filled out a similar questionnaire and added how many lessons they had received prior to the study. Both the instructors and students signed an informed consent. The participants agreed to be video- and audio recorded and were free to see the data and request data removal. It was stressed that the video's would not be distributed.

2 GoPro Hero 4 video cameras and 1 microphone were used. Each camera filmed with a wide angle ("Superview") at a resolution of 1920*1080. Camera 1 filmed the passenger and driver, while camera 2 filmed the outside environment through the front windscreen (Figure 6.1). The instructor was equipped with a microphone to ensure quality audio in situations with a lot of traffic noise. All cars were owned by the participating driving schools and were equipped with secondary brake- and clutch pedals for the instructor's seat. This is required by the Dutch law for all driving instructor vehicles. While the car models varied per driving school, none of the cars were equipped with automated technology such as Adaptive Cruise Control.

Figure 6.1. Example of the videos recorded during the driving lessons.

6.2.3 Procedure

First, participants were informed about the main procedures. The driving lessons started after filling out a demographics questionnaire. The researcher sat in the back of the car to note any events that may be difficult to see on camera. All instructors were asked to conduct their driving lessons as per usual and include both highway and city scenarios if deemed appropriate. Driving instructors were further asked to support their student as usual and to refrain from talking to the researcher in the back. Instructors were then filmed during one to three lessons of 50 minutes

each, depending on availability. At the end of the filming day, the driving instructors were asked whether and how the driving instructor's feedback adapted to the driving situation and the student. All instructors received a small present for participating.

6.2.4 Variables and labelling procedure

Complexity of the environment. Each second of the video recordings was manually annotated by two researchers to indicate the type of driving situation. As described earlier, it was decided to note the overall complexity of the driving situation as this may have serious effects on the driver's feedback need. How the complexity of a driving situation may exactly be determined is investigated in more detail in Chapter 7. The base for the final coding scheme was the work by Fastenmeier (1995). In this work, Fastenmeier combined previous research on driving situations, for example by Benda (1977), and condensed it into a concise road type schema. The authors rated each road type on the required information processing, complexity of the vehicle handling and an overall (combined) complexity. As this schema only took the infrastructure into consideration, some adaptations had to be made. Our study described in Chapter 7 showed that several traffic characteristics needed to be added to the coding schedule to determine the overall complexity of driving situations. Elements that would increase the complexity were: road users that violated traffic rules, bad visibility either through weather or blocking objects, road works, and objects or road users blocking the road. The following steps were followed in the final scheme during the coding of the environment to determine the complexity of the situation. First, the road type was determined. Then, the priority rules, travel direction and intersecting road users were assessed. Last, any special conditions that would add to the complexity were determined (e.g. weather, visibility, road works, obstacles). These steps would lead to the final complexity score of the driving situation (1 low to 3 high). Although too extensive for this manuscript, the complete labelling schedule can be accessed on the open data sharing platform OSF through the following link: [OSF.IO/7JRKH](https://osf.io/7JRKH).

Verbal and non-verbal communication. All behaviour and speech was categorized to examine the communication by the driving instructors (Table 6.1). The specific gestures and speech related to the overall categories are presented in Appendix D.1. The overarching categories were based on other ethogram-based studies on teaching such as that by Kline (2017). The categories in that study were adapted and complemented during an initial pilot coding session of the first hour of video.

While behaviour events only had a start timestamp, each speech event had a start- and end time. Each time the category (or goal) of the speech changed, the current speech event was ended and a new one was created. Furthermore, any speech event was ended if the instructor stopped talking

for more than one second. Besides the categorization, all speech was further examined by the duration and word count of each speech event.

Table 6.1.

An overview of all categories that were used to label all behaviour- and speech events.

Behaviour- and speech categories
1) Feedback
Positive
Negative
2) Direct Attention
3) Indicate Desired Behaviour
4) Reflect on previous situation
5) Reflect on current situation
6) Explain basic traffic rules
7) Explain car equipment
8) Test theory knowledge
9) Non-driving related

6.2.5 Data analysis

As the speech and behaviour events were count data, chi-square tests were performed to identify a relationship between the speech/behaviour categories and the complexity of the environment. Furthermore, as the word count and duration per speech event were not normally distributed Kruskal-Wallis tests had to be performed to identify differences of these variables among the environment complexities. A relationship between the number of the student's driving lessons at the start of the study (driving experience) and the word count per speech event was examined through a Spearman correlation. The same was done for the duration per speech event. The small sample size for the Spearman correlation needs to be taken into account when interpreting the results.

As the driving complexity was rated for each second of the videos, a large amount of data points ($N = 63951$) were used in the analysis. We therefore decided to have an additional annotator label 10% of the driving situation data and check the interrater reliability. As 86.3% of the complexity data was rated the same, a Cohen's Kappa score of .643 ($p < .001$) showed a substantial agreement (Landis & Koch, 1977). The same procedure was followed for the speech data resulting in a moderate agreement of $\kappa = .452$ ($p < .001$). As the behavioural data was smaller ($N = 1247$), the second rater rated all data and any differences were discussed and resolved. Tests of normality (Kolmogorov-Smirnova) determined that both the word count ($D(5304) = .324$, $p < .001$) and speech duration ($D(5304) = .338$, $p < .001$) had to be analysed through non-parametric tests as both data was not normally distributed. Histograms showed right-skewed data for both variables.

6.3 Results

A total of 17.5 hours of video and audio data were available for analysis (1048 minutes). Each instructor was filmed an average of 131 minutes ($SD = 29$, range = 86-171).

6.3.1 Behaviour

In the observation videos, a total of 1247 behaviour events were identified. These events consist of gestures and full body movements. The number of behaviour events per student ranged rather widely between instructors ($M = 90.63$ $SD = 60.63$, range = 32-235). The majority of these events occurred in low complex situations (65.3%), while 20.4% occurred in medium and 14.3% in highly complex situations. Most of the observed gestures were to indicate a desired behaviour (28%) or direct the attention of the student (26.1%). Reflecting on previous (14.3%) or current situations (11.5%) and explaining the general traffic rules (11.6%) were used a similar amount. Least used gestures were to explain the equipment (4.3%), give positive or negative feedback (3.3%) and to test theoretical knowledge of the student (1%).

Figure 6.2 shows a clear difference of the distribution of behaviour categories among the different environment complexities. A chi-square test confirmed a relation between the behaviour category and environment complexity ($\chi^2(14, N = 1247) = 122.75, p < .001$). It appears that gestures that request an actions (such as “brake”) and/or gestures that direct the attention of the student to a specific event, occur more frequently in medium and highly complex situations. Especially gestures used to reflect on previous or current situations as well as those used to explain traffic rules decrease with an increase in complexity. A post-hoc Bonferroni analysis was conducted with an adjusted alpha level of .00208 as each of the different behaviour types was tested. This analysis confirmed that instructors showed more gestures that indicated a desired behaviour in highly complex situations compared to medium ($p < .001$) and low complex situation ($p < .001$). More gestures to reflect on a previous situation ($p = .001$) and to explain basic traffic rules ($p < .001$) were observed in low complexity situations compared to highly complex situations.

Figure 6.2. Observed behaviour for all driving situations of varying complexity level.

6.3.2 Speech

A total of 5304 speech events were obtained from the video data. On average, the instructors had 350 speech events per student ($SD = 102.00$, range = 237-537). As with the behaviour events, the majority of the speech events took place during low complex situations (59.9%). 20.7% occurred during medium and 19.3% during highly complex situation. Most of the speech was used to reflect on the current (25.7%) or previous (17.3%) situation. While there was little behavioural feedback, the speech contained 18.7% of feedback which mainly consisted of short appraisals such as: “well done”. Indicating a desired action was also used often (18.6%), while directing the students attention (9.1%), explaining the traffic rules (7.1%), explaining the equipment (1.9%) and testing theory knowledge (1.6%) were less frequent. Figure 6.3 shows a similar patterns in the speech events compared to the behaviour events. Still, the differences between low and high complexity appear smaller. The verbal reflection of current and previous situations, as well as the discussion of general traffic rules appear to decrease as the environment complexity increases. Both indicating behaviour and giving positive or negative feedback seem to increase with increasing environment complexity. A chi-square test confirmed a relationship between the speech events and environment complexity ($\chi^2(14, N = 5304) = 219.8, p < .001$). A post-hoc Bonferroni with an adjusted alpha of .00208 showed that instructors explained basic traffic rules more frequently in low complex situations compared to highly complex situations ($p < .001$). Explaining the car equipment ($p < .001$) and testing theory knowledge ($p < .001$) was done more in low- compared to medium complex situations. Reflecting on previous situations was more

frequent in low- compared to highly complex situations ($p < .001$). Indicating a desired behaviour was more frequent in high ($p < .001$) and medium ($p < .001$) compared to low complex situations.

Figure 6.3. Observed speech events for all driving situations of varying complexity level.

Next, we examined whether and how the word count and duration of each speech event related to the complexity of the environment. The average word count per event appeared to decrease as the complexity of the driving situation increased (Table 6.2). In the low complex situations the average word count per event was 10.9 ($SD = 23.7$) which dropped to 9.2 ($SD = 11.1$) for medium and 7.4 ($SD = 8.5$) for high complex situations. A Kruskal-Wallis test confirmed a relation between word count and the environment complexity ($\chi^2(2) = 49.4, p < .001$). Following Mann-Whitney tests confirmed that the word count was different for all complexity levels ($p < .01$).

The duration of each speech event also appeared to decrease as the complexity of the driving situation increased (Table 6.2). The low complex situations show an average of 3.4 seconds per speech event ($SD = 8.1$), while the medium and high complex situations have an average of 2.9 ($SD = 3.2$) and 2.4 seconds ($SD = 2.8$) per speech event. A Kruskal-Wallis test confirmed a relation between the duration per speech event and the environment complexity ($\chi^2(2) = 28.6, p < .001$). The duration in highly complex situations was significantly higher than in the low ($U = 1453407, p < .001$). and medium complex situations ($U = 516895, p = .001$). However, no difference in duration per speech event was found between medium and low complex situations ($U = 1702690, p = .117$). Scatterplots appeared to indicate lower durations and word counts of speech events for students with more driving experience. However, the correlations were not found to be significant ($r_{\text{WordCount}} = -.23, p = .421, r_{\text{Duration}} = -.364, p = .20$).

Table 6.2.

Overview of the average word count and duration per speech event over the different level of driving situation complexities.

	Low complexity (N = 3180)			Medium complexity (N = 1100)			High complexity (N = 1024)		
	M	SD	95% CI	M	SD	95% CI	M	SD	95% CI
Word count per speech event*	10.90	23.70	10.08 - 11.72	9.20	11.10	8.54 - 9.86	7.40	8.46	6.88 - 7.92
Duration (s) per speech event **	3.42	8.10	3.19 – 3.75	2.85	3.18	2.66 - 3.04	2.41	2.75	2.24 - 2.58

Note. * Significant difference between low-medium, medium-high and low-high $p < .01$. ** Significant differences between low-medium and low-high $p < .001$.

6.3.3 Qualitative results: feedback patterns

During the observations, the experimenter took note of recurring feedback patterns by the driving instructor which were re-examined during the video analysis. The findings are summarized below.

Student adaptive tasks. Driving instructors would deliberately guide the student towards areas that contained core elements with which the student struggled. The instructors confirmed this after the lessons. A student that struggled with sharp turns and smooth braking was guided towards a residential area that had eight consecutive roundabouts. Students that had trouble with ‘thinking ahead’ were routed towards areas that required merging towards the right lane well before the intersection where they needed to turn.

Student adaptive feedback. The timing of the feedback appeared to depend on the experience of the student. Inexperienced students were informed about difficult upcoming situations, and how to handle them, well in advance. While most instructors provided this information verbally while driving, some instructors let their students stop and drew the situation, acted it out with props or showed an instruction video on a tablet. Experienced students however would first experience the difficult situation without help, after which the instructor would ask the student himself to reflect on the situation and their actions. Only thereafter would the instructor give their own additional feedback. Still, if experienced students would make the same mistake multiple times, the instructor would start to announce similar situations in advance.

Almost all lessons started with elaborate feedback by combining speech, gestures and body movements. As time progressed, the instructor would transfer to the use of only speech or only gestures for their feedback. Still, the messages would remain comprehensible as they were a

repetition of prior feedback (i.e. slow down, look in your mirrors). Similarly, the amount of feedback appeared to be higher for students with less driving experience.

Situation adaptive feedback. Instructors would use the current simple environment as a base to discuss hypothetical critical situations. For example, while passing a simple grade intersection, the instructor may ask the student what he would have to do if a motorcycle would approach from the right. Furthermore, the instructors would address why the current situation was different than ‘normal’, and how that affected the actions the student needed to take. This included errors by other road users, but also the weather and road conditions.

Correcting/requesting behaviour through gestures, body movement and speech. It was frequently observed that the instructor would seize all verbal communication, sit upright and raise a finger or hand in case an upcoming situation was highly complex and required full attention. Instructors would ask questions about the current situation to indicate an error. For example, an instructor would ask: “What is the speed limit here?”, to indicate that the student was speeding. Gestures and body movements were also frequently used to indicate an error. In case the student forgot an action, some instructors would give a soft nudge combined with a gesture about the error. Exaggerated full body movements were mainly used to indicate: speeding, driving too slow, steering too abruptly and taking too sharp turns. Exaggerated turning of the head to the right, left or back was done to request (better) looking behaviour of the student.

Reassurance. Instructors sometimes downsized error by the student to reassure them. They would indicate that the error was not that bad, they should not worry too much, and that it is a good opportunity to learn. Furthermore, the instructor would verbalize correct actions by the student. Lastly, full body movements were used to calm the students down. These included slow wave-like motions with body and hands, but also taking a deep breath while raising and then lowering the hands.

6.4 Recommendations, discussion and conclusions

In the following section, recommendations for an adaptive and naturalistic Digital In-Car Tutor (DIT) are presented. The recommendations include both the qualitative and quantitative results of this study.

6.4.1 Student adaptive tasks

A DIT may need to assess the knowledge about, and experience with, car automation of the driver. This way, it can reroute through areas with (non-critical) road situations so the driver gets to update their knowledge about these specific types of situations. Furthermore, situations

that have not occurred for a long time may need to be incorporated in the route to keep the drivers' knowledge up-to-date (Beggiato, Pereira, et al., 2015). This strategy was observed during this observation study and in studies from both transportation- (Ropelato et al., 2017) and other domains (Leyzberg et al., 2014; Niehaus & Riedl, 2009). Still, rerouting to unfamiliar situations may create a unnecessary safety risks.

6.4.2 Student adaptive feedback

For inexperienced drivers, complicated situations are suggested to be discussed beforehand. For experienced drivers, discussion on complex situations should take place after the fact to stimulate critical thinking and self-reflection. This is in line with the fact that inexperienced drivers usually struggle with efficiently dividing their attention and anticipating (Fisher, Pollatsek, & Pradhan, 2006; Lee, 2007). Furthermore, tutor feedback may need to become less elaborate as drivers gain experience. This is often referred to as fading scaffolding (Belland, 2013). However, our quantitative analysis could not confirm a significant relationship between driving experience and feedback duration. As, additional studies may be necessary. Additional studies on this may be necessary as our sample for this particular analysis was small. Last, if a driver unnecessarily takes back control repeatedly in a specific situation, the DIT may start to announce these situations shortly ahead of time. This holds for both inexperienced and experienced drivers.

6.4.3 Situation adaptive feedback

The results of this study suggest to adapt the tutor feedback to the complexity of the driving situation in multiple ways. Any reflection on previous and current situations should be reserved for low complex situations. The same holds for the discussion of general traffic rules and for giving general information about the car equipment. On the other hand, highly complex situations require more action oriented feedback. This includes directing the attention of the driver but also requesting particular actions. The results further suggest a need to adapt the overall length of verbal feedback (word count and duration) to the complexity of the situation. These implementations may avoid overloading of the driver in complex situations.

A DIT is advised to discuss hypothetical rare situations that are relevant to the current driving environment. This way knowledge about the automation may be transferred to situations that are rarely encountered. For example, while driving on a quiet roundabout, it may discuss what the driver would need to do if an emergency vehicle were to approach from the back. Furthermore, when driving in rare conditions such as heavy rain, a DIT may address how the current situation is different than normal and how the automation's behaviour may change accordingly.

A DIT is further advised to block any non-driving related communication and/or activities in

highly complex situation that require direct attention (and possible a take-over) by the driver. For example, connected phones and other media displays in the car may be temporarily disabled (Melcher et al., 2015).

6.4.4 Correcting/requesting behaviour through gestures and body movement

Based on the results it is recommended to include gestures and full body movement into feedback in order to: 1) strengthen a correction, 2) request an action or 3) direct the student's attention. The gestures and body movements may be mimicked through a variation of methods. One option is to include gestures and body movement through an avatar (Hock et al., 2016). This digital persona can visually perform any gestures or body movements an instructor would normally do. Other options are the incorporation of the movements into a physical device, or by adapting the vehicle dynamics. For example, a request for attention can be issued by shortly braking the car (Melcher et al., 2015) or by a physical device that gives a nudge.

6.4.5 Reassurance and social cues

A DIT is recommended to reassure the driver after observed errors such as an unnecessary take-over. This can be done verbally but also through the mimicking of reassuring body movements. For example though wave-like patterns in the in-car lighting or smoother braking and accelerating. Furthermore, a DIT is suggested to praise the driver occasionally after successful actions. This can be done by alternating between short positive feedback such as 'well done', and positive step-by-step reflection of the previous situation. All of these elements may contribute to a safe and comfortable (learning) environment, which is necessary to invest in building a social bond between the driver and tutor system (Breazeal et al., 2005; Castellano et al., 2013). The exact frequency of the cues need to be determined as too many may actually create annoyance and hinder learning (Kennedy et al., 2015).

6.4.6 Considerations for future work

Several considerations regarding this study and future work need to be noted. We recognize that individual instructors may have different communication styles, and that not every style will be well received by students. While this study did not yet investigate the effect of different feedback strategies on acceptance and driving style, this needs to be further investigated. Second, it is unclear how drivers will react to a digital tutor compared to a human tutor, and whether they will be similarly cooperative (Agrawal & Williams, 2017; Cormier, Nakane, E., & Durocher, 2013). Future investigation may need to identify if adaptations to the identified feedback strategies are necessary in a DIT to create acceptance and cooperation in drivers. Last, it is possible that the relationship between situation complexity and reduced feedback (duration and word count) is a

direct result of the increased workload of the instructor. A follow up study needs to assess whether complexity adaptive feedback in a DIT actually helps to avoid overload of the driver.

6.4.7 Conclusions

A Digital In-Car Tutor (DIT) is proposed to support drivers in the initial use period of (partially) automated cars, so they can create and maintain accurate mental models of the automation. This DIT will need to be adaptive to the driving situation and experience of the driver to create an optimal learning environment. In this study we examined the natural verbal and non-verbal tutoring strategies of driving instructors during driving lessons. It was found that instructors indeed adjust feedback type according to the complexity of the driving situation. More direct and action based feedback was observed in highly complex situations while reflective feedback mainly occurred in low complex situations. Furthermore, the overall length and extensiveness of the verbal feedback was lower for highly complex situations. Instructors not only adapted their routes and tasks to the experience of the student, but also the timing, length and depth of their feedback. Overall, we will use the results of this study as an inspiration for the development and evaluation of an adaptive and naturalistic DIT in (partially) automated cars.

Chapter 7

Determining complexity of driving situations for an adaptive Digital In-car Tutor

This chapter is based on:

Boelhouwer, A., Van den Beukel, A.P., Van der Voort, M.C., & Martens, M.H. (2020). Determining Environment Factors That Increase the Complexity of Driving Situations. In N. Stanton (Ed.), *Proceedings of the AHFE 2020 International Conference on Human Factors in Transportation* (pp. 3-10). Springer, Cham. doi: 10.1007/978-3-030-50943-9_1

The data of this study is freely available at:

www.OSF.IO/QAMDB

Chapter 7. Determining complexity of driving situations for an adaptive Digital In-Car Tutor

7.1 Introduction

In the previous chapter, we have investigated how driving instructors adapt their tutor strategies to their students and (the complexity) of the driving situation. The results of that study will be used as inspiration for the design of an adaptive Digital In-car Tutor, which strives to guide drivers in understanding and using the automation in their car. We determined that drivers need information that is adaptive to the environment as their processing capability is dependent on the complexity of the driving situation (Kroon et al., 2016; Mueller, 2014). Information interfaces in the car need to be adaptive in these situations to avoid overloading the driver. For example, drivers may require more condensed or simplified information from the HMI in highly complex situations. However, in order to conduct the observation study, and to be able to determine the complexity of the driving situation, it was necessary to examine which infrastructure- and traffic elements contribute to the perceived complexity of the driving situation. While other studies (Lyu et al., 2017; Radlmayr et al., 2014) have investigated the effect of one specific road- or traffic element on drivers' mental workload, there was no condensed overview of elements which may contribute to the overall complexity when designing scenarios. Also, the listed studies mainly focused on highway scenarios. It was unclear how the results translate to urban and rural scenarios. The work by Fastenmeier (1995) presents a great base for defining the complexity of road sections and will be used as the foundation of this research. Still, this research only focusses on the infrastructural aspects but not the variation in traffic.

The goal of this study was therefore to identify core environment characteristics that contribute to the overall complexity while creating and validating a set of reusable scenarios of varying complexities. This was achieved by applying various infrastructure- and traffic characteristics found in literature to five basic road types (straight, curve, intersection, roundabout, highway). These were then rated on their overall-, infrastructure- and traffic complexity in an online survey.

7.2 Methods

The road analysis schema described by Fastenmeier (1995) was used as a base to create scenarios of different complexities for both urban and highway settings. This schema is based on both the physical and mental processing load of a driver in specific infrastructure sections. Based on other studies like those by Radlmayr et al. (2014) and Zeitlin (2006) we added several traffic- and infrastructure characteristics to the scenarios. An overview of all scenarios can be found in Figure 7.1. Then, an online survey was conducted to assess the complexity of driving scenarios, and

the elements that may increase the complexity. In this survey, participants rated each scenarios on its overall-, traffic- and infrastructure complexity. Each scenario was presented as a top view illustration to the participants as depicted in Figure 7.1.

7.2.1 Participants

A total of 143 respondents completed our online survey. As the survey was distributed on the American online crowdsourcing platform MTurk, all respondents were from the US. The youngest respondent was 21 years old, while the oldest was 73 years old ($M = 34.06$, $SD = 8.83$). 51% of the respondents was male and 49% was female. The education level was relatively high with 58.1% having at least a bachelor's degree. Respondents were required to have a driver's license to be able to participate. The majority (76.2%) had had their driver's license for more than 10 years, 18.2% had it between five and 10 years and 5.6% had it for less than 5 years.

7.2.2 Scenarios

Infrastructure. Five frequently occurring base scenarios were chosen: straight road, curve, intersection, roundabout and highway (Figure 7.1 column a). The road analysis schema by Fastenmeier (1995) was subsequently used in order to vary the infrastructure complexity of these five base scenarios. This schema clusters road elements on their physical and mental processing load. The work of Fastenmeier (1995) is an integration of own research and prior work by (amongst others) Benda (1977) and Hackman (1970). In the schema by Fastenmeier (1995), certain road elements either increase or decrease the complexity for the driver. Road elements that increase the complexity according to the schema are: sharp turns, slopes, obstacles, road narrowing, absence of road lines, and having to give priority regulated by signs. Elements that should relieve the load of drivers are unobstructed views, signalized intersections (instead of priority to the right or signed priority) and separated lanes by for example a centre divider. Other elements that may increase the complexity are unique or unfamiliar road constructions. Similarly, the study by Matthews et al. (1999) showed increased stress when encountering unfamiliar road situations. Therefore, we included a Dutch style roundabout with integrated bicycle paths. This was expectedly an unfamiliar sight for the respondents that were from the US. To create scenarios of higher infrastructure complexity the workload inducing elements were applied to the five base scenarios (Figure 7.1 column b).

Figure 7.1. The constructed scenarios: a) base scenarios, b) base and added infrastructure complexity, c) base and added traffic d) traffic- and infrastructure changes combined.

Traffic. Next, traffic was added to the base scenarios (Figure 7.1 column c). Several traffic factors may influence the complexity of a driving situation. First, prior studies like that of Radlmayr et al. (2014) and de Waard (1991) have already shown the effect of traffic density on drivers' mental workload. Still, there are other traffic related factors that can make driving situations more or less complex for the driver. A second important overall factor is the predictability of other road users. The predictability of other road users showed to have a large impact on the perceived difficulty of a driving situation (Zeitlin, 2006). Unpredictable traffic behaviour may include road users that break traffic rules. Furthermore, the variety in road user types and differences in travel direction can decrease predictability and increase the situation complexity.

To create situations of higher traffic complexity, the factors of traffic density, traffic predictability and giving priority without support were applied. For the traffic density, the number of road users was increased. For the predictability, a variety of road user types, travel directions and road users that break the rules were included. To include priority without support, road users were included that should receive priority from the ego vehicle. Lastly, both the infrastructure- and traffic adaptations were combined to create the last scenarios (Figure 7.1 column d).

7.2.3 Materials and procedure

This experiment consisted of a survey distributed through an online crowdsourcing platform by Amazon, MTurk. This platform allowed us to gather a large amount of respondents relatively fast for a small compensation (Casler, Bickel, & Hackett, 2013). The average completion time of the survey was 24 minutes. Each participant was compensated \$2 for their time. The start of the survey contained four demographics questions regarding the respondents age, gender, driver's license and education level. The questionnaire contained 18 different scenarios, each was displayed at random and twice in the experiment. Each scenario was rated on the overall-, infrastructure- and traffic complexity. The answer scales ranged from 1 (very simple) to 9 (very complex).

7.3 Results

7.3.1 Overall complexity

First, the overall complexity of each of the five basic road types (straight, curve, intersection, roundabout, highway) were inspected without any infrastructure- or traffic additions. The base straight, curve and highway scenarios scored relatively low with respective overall scores of $M_{Straight} = 1.4$ ($SD_{Straight} = 1.32$), $M_{Curve} = 1.7$ ($SD_{Curve} = 1.39$) and $M_{Highway} = 1.8$ ($SD_{Highway} = 1.39$). The intersection and roundabout scenarios appeared to have higher scores with $M_{Intersection} = 2.3$ ($SD_{Intersection} = 1.52$) and $M_{Roundabout} = 4.1$ ($SD_{Roundabout} = 1.39$). A One-way ANOVA confirmed that the road types scored differently on their complexity ($F(4,710) = 70.22, p < .001$). Following t-tests showed that all base road types were significantly different from each other (all $p < .05$), just the highway and curve scenarios were not scored differently from each other ($t(284) = -.43, p = .67$).

Following, it was analysed whether the traffic and infrastructural changes that were applied to increase the overall complexity actually increase the overall scores. The base scenarios scored an average of $M_{Base} = 2.3$ ($SD_{Base} = 1.22$). The scenarios that had their infrastructure changed to increase complexity were scored an average of $M_{Infrastructure} = 3.6$ ($SD_{Infrastructure} = 1.35$) while the scenarios with changed traffic scored an average of $M_{Traffic} = 3.7$ ($SD_{Traffic} = 1.22$). The scenarios that combined the infrastructure and traffic changes scored an average of $M_{Combined} = 5.2$ ($SD_{Combined} = 1.20$). Figure 7.2 shows an overview of the complexity scores for all scenarios.

A One-way ANOVA confirmed that the base-, infrastructure-, traffic- and combined scenarios were scored differently ($F(3,568)=128.67, p < .001$). Paired t-tests showed that the base scenarios were scored significantly lower than the infrastructure ($t(142) = -17.80, p < .001$), traffic ($t(142) = -19.02, p < .001$) and combined scenarios ($t(142) = -27.12, p < .001$). The infrastructure and

traffic altered scenarios were not found to be different ($t(142) = -1.34, p = .18$). Still, both the infrastructure ($t(142) = -16.58, p < .001$) and traffic ($t(142) = -20.17, p < .001$) altered scenarios were scored lower than the scenarios in which the infrastructure and traffic changes were combined.

Figure 7.2. Overview of the complexity scores for all scenarios.

7.3.2 Influence of Infrastructure- and Traffic Complexity on Overall Complexity

It was unclear to what extent the infrastructure and traffic contributed to the overall complexity of the scenarios. As each scenario was scored on the infrastructural-, traffic- and overall complexity, this could be analysed through a multiple regression model. Scatterplots confirmed linear relationships between the infrastructure complexity scores and overall complexity scores. The same was found for the traffic complexity scores and overall complexity scores. Multicollinearity was not of concern (TrafficComplexity, Tolerance = .267, VIF = 3.74; InfrastructureComplexity, Tolerance = .267, VIF = 3.74). First a regression model with only traffic complexity scores as a predictor was created. This model showed that the traffic complexity scores explain the overall complexity scores well with an R^2 of .77 ($F(1,141) = 464.032, p < .001$). Following, the infrastructure complexity scores were added as a predictor. In this combined regression model, the infrastructure- and traffic scores explain the overall complexity very well with an R^2 of .86 ($F(2,140) = 431.153, p < .001$). In this model the overall complexity score is equal to $.261 + .357 (\text{InfrastructureScore}) + .594 (\text{TrafficScore})$. Increased traffic complexity scores appear to contribute to overall complexity scores more than infrastructure.

7.4 Discussion

During this study, we identified several infrastructure- and traffic elements in literature that were proposed to increase the perceived complexity of a driving situation. The infrastructural elements

included: sharp turns, slopes, obstacles, road narrowing, absence of road lines, unfamiliar constructions and having to give priority regulated by signs. Traffic elements that were used to increase complexity were based on several studies and included: traffic density, varying road user types, multiple travel directions of other road users, road users that break the traffic rules and having to give priority without infrastructural support. These elements were integrated into multiple scenarios of varying complexity and validated through an online survey.

The results of this study show that both the infrastructural- and traffic changes indeed increased the overall complexity of scenarios. By combining these infrastructure- and traffic elements the overall complexity increased even further. While both contribute to the overall complexity, it is noteworthy that the traffic had a larger influence compared to the infrastructure. When constructing scenarios that need to be of high complexity, it therefore seems advisable to focus on (but not solely rely on) introducing traffic elements.

Interestingly, not only the infrastructural- and traffic changes contributed to the overall complexity of the scenarios. The overall complexity changes also based on the core road type (straight, curve, intersection, roundabout and highway). Curved roads were perceived as the least complex followed by the straight roads. Intersections and highways were considered slightly more complex. The roundabout scenarios were perceived to be more complex than the other scenarios. As described earlier, unfamiliarity may increase the complexity of a scenario. This may have contributed to the increased complexity as the respondents were American. Roundabouts, especially with dedicated bicycle lanes, are still relatively new in the US compared to in European countries. There are some elements that may further increase (or decrease) the complexity of driving scenarios that were not included in this study such as non-road environment, weather and communication by other road users. A city environment with highly dense and variable building is more complex to process compared to a rural road surrounded by similar meadows. Furthermore, verbal and behavioural communication by other road users can increase complexity.

Concluding, we identified infrastructure- and traffic elements that contributed to the overall complexity of driving situations which can be used to create new scenarios of varying complexities for driving studies. Furthermore, the study presents a validated selection of driving situations of varying complexities. The results of this study are particularly useful to further study and develop adaptive driver feedback and support systems in (partially) automated cars.

Chapter 8

Evaluation of an adaptive Digital In-car Tutor

This chapter is based on:

Boelhouwer, A., Van den Beukel, A.P., Van der Voort, M.C., Verwey, W.B., & Martens, M.H. (2020). Supporting Drivers of Partially Automated Cars Through an Adaptive Digital In-Car Tutor. *Information*, 185, 1-22. doi:10.3390/info11040185

The data of this study is freely available at:

www.OSF.IO/XEBRW

Chapter 8. Evaluation of an adaptive Digital In-Car Tutor

8.1 Introduction

Several solutions have been proposed to support drivers in understanding, and safely using, the automation in their car. The first one is to stimulate the use of owner's manuals. However, not only are these usually long and complicated, multiple studies (including our own in Chapter 4) suggest that practice is required to fully support safe automation use (Boelhouwer et al., 2019b; Forster, Hergeth, Naujoks, Krems, & Keinath, 2019; McDonald, Reyes, et al., 2016). This practice could be done at driving schools or in driving simulators. Especially driving simulators allow drivers to practise with rare but critical driving situations (Panou et al., 2010; Payre et al., 2017; Ropelato et al., 2017). The main downside to these options is that additional training at a driving school or at a facility with a simulator requires a high investments, both financially and time wise. In the present study we therefore explore the potential of a Digital In-car Tutor (DIT) to guide drivers during regular drives in learning about, and safely using, the automated functions in their cars.

8.1.1 Digital In-car Tutor

A Digital In-car Tutor (DIT) is a digital tutor that guides drivers through the different automated systems in their cars during regular driving trips. While a DIT may take various forms (e.g. Simon, 2005), we particularly studied a DIT for its potential merits to provide long-term, in-situ and adaptive tutoring on the vehicle's automation. The following three steps illustrate the core functionalities of a DIT. First, the DIT introduces one of the automated car systems while the driver is driving manually. Of course, new systems are only introduced when the driver is in a low complex situation (Boelhouwer, van den Beukel, van der Voort, & Martens, 2020), like an empty straight road on a clear day. The introduction includes the system's functionalities, handling, capabilities and limitations, and equipment. Second, the driver can try out the functionality while the DIT provides immediate feedback. Third, the DIT reminds drivers about specific systems capabilities and limitations when a related situation is encountered. Rare situations may be addressed when driving in similar situations that occur more regularly to keep the driver's mental model up-to-date (Beggiato, Pereira, et al., 2015). Only after the driver has safely driven with the automated function for a certain amount of kilometres (for example 500 km), a new system is introduced and the cycle repeats itself.

A DIT could have many benefits over regular driving lessons and the use of owner's manuals. First, it is less time consuming and costly, as it is active during regular drives. Second, a DIT allows for continuous and situated support over a longer period of time. Last, a DIT can be brand- and model-specific. If automated functions are changed by software updates this can be automatically

incorporated in the DIT. In order to test the DIT, a tangible prototype was developed based on Augmented Reality (AR) overlay on the windscreen and audible feedback. An explanation of this design is presented in section 8.2.4.

8.1.2 Adaptive communication

To facilitate learning, and avoid excessive cognitive demands, a DIT should be adaptive in multiple ways. First, driver-system communication should be related to the current driving situation so the driver can process the information more easily and directly apply it. Furthermore, the modality, timing and duration of the communication needs to adjust to the demand of the driving situation to avoid overload. Studies on the cognitive demands of feedback suggest that tutoring in highly complex driving situations should be condensed and action-based. Elaborate theory and reflection can be presented during low complexity situations (Boelhouwer, van den Beukel, Casner, Van Der Voort, & Martens, *Under review.*; van Gent, Farah, van Nes, & van Arem, 2019; Wilkison, Fisk, & Rogers, 2007). Last, the feedback needs to adapt to the driver's performance, to update his or her mental model. This includes both direct but short feedback, and elaborate reflection after the situation. For example, the driver may need to be informed if they turn on the automation outside of its Operational Design Domain (Forster, Hergeth, Naujoks, & Krems, 2019).

The research by Simon (2005) already studied an auditory digital tutor for Adaptive Cruise Control (ACC). The tutor content was adaptive to the traffic situation in general and the driver's preferred maximum deceleration. However, the timing and duration did not adapt, nor was the information adjusted to the complexity of the traffic situation. These characteristics however may be required in a tutor system as it may help to prevent driver overload. Simon (2005) showed positive effects of the tutor on driving safety and more efficient use of the ACC. However, we need to extend this research towards cars with multiple automated systems as this drastically increases the learning difficulty for drivers.

8.1.3 Present study

In the current study, we compared the effects of a DIT prototype (DIT group) and information brochure (IB group) on the use of complex car automation during three driving sessions in a driving simulator. In all driving scenarios, participants needed to decide whether they could use the automation or not. In scenarios that required the automation to be off, the take-over quality was analysed. Multiple acceptance elements (e.g. ease of use) of both the training method and the automation were assessed through questionnaires. During the first driving session, the experimental group (DIT group) was supported by the DIT prototype in learning about the various automated car systems. The control group familiarized with the automation by reading an information brochure (IB group) before driving in the simulator. Two more driving sessions

followed, one directly after the first and one after two weeks. During these sessions, the DIT was no longer active for the DIT group.

Overall, we expected the DIT to provide drivers with a better understanding, and safer use, of the automation. Our first hypothesis was that using the DIT would result in more appropriate automation use. That is, drivers would only rely on the automation if it could deal with the situation safely, and take back control if it could not. A second hypothesis was that drivers were expected to show better take-over performance in critical situations. Better take-over performance was defined as: taking-over earlier, braking less intensely, and more stable vehicle control. In conclusion, we examined whether a DIT, is more beneficial for supporting drivers in learning about, and safely using, the automation in their car, than when they are using a brochure and have to learn in practice.

8.2 Methods

8.2.1 Participants

38 participants (23 female, 15 male) took part in the driving simulator study. 19 participants were part of the control condition (IB group) and 19 of the experimental condition (DIT group). All participants were students or employees of the University of Twente. Their average age was 27.5 years ($SD = 13.1$ years, range = 18-65 years). On average, participants possessed their driver's license for 9.2 years ($SD = 10.81$, range: 1-47). 8 participants drove almost every day and 15 drove multiple times a week. 8 participants drove once a week and 7 less than once per week. Most had experience with Cruise Control ($N = 29$). 7 participants had experience with Adaptive Cruise Control and 2 with Lane Assist. The Affinity for Technology Interaction (ATI) scale (Franke, Attig, & Wessel, 2018, 2019) was used to determine the level of general affinity with technology of the participants. On this scale of 1 (low affinity with technology) to 6 (high affinity with technology), the participants scored an average of 3.9 ($SD = .77$). The groups did not significantly differ on any of these characteristics. Participants had to speak and understand English fluently to be able to participate as the experiment was conducted in English.

8.2.2 Materials

The experiment took place in the driving simulator of the University of Twente (See Section 1.2). This simulator includes a car mock-up with steering wheel and pedals. Three beamers project the simulation on a 7.8m by 1.95m screen with a view angle of approximately 180 degrees. Rear- and side mirrors are projected on the screen. A tablet was used to display the speedometer, RPM indicator, and an icon to show whether the automation was on. The simulated car was equipped with level 2 automation which included 1) Adaptive Cruise Control (ACC), 2) Lane

Centring (LC), 3) Obstacle Detection (OD), 4) Traffic Light and Priority Sign Detection (TS), and 5) Priority Road Markings Detection (RM). These systems were designed specifically for this experiment and did not resemble a particular car model to prevent transfer of knowledge about existing cars as much as possible as this may influence the interaction. Participants were informed about this. The steering wheel included a blue button to turn all automation on and off. Due to technical limitations, participants could not turn the automation off by braking or steering.

8.2.3 Experimental condition: Brochure training (IB group)

At the start of the first driving session, participants in the IB group received a paper brochure on the five automated systems. They read this information for 10 minutes before driving. This brochure included the functions, handling, equipment, capabilities and limitations of each systems. It contained the same system information that the DIT group received from the DIT. However, as the information was given prior to the practice scenarios it did not include any situation specific feedback nor any feedback tailored to the driver's performance (i.e. the decision to utilize the automation or not).

8.2.4 Experimental condition: Digital In-car Tutor (DIT group)

As discussed earlier, a DIT gradually guides drivers in learning about the automated functions in their car during regular trips. In order to practically evaluate the concept of a DIT, we developed a prototype in our driving simulator. In this section we will discuss the DIT prototype that was used in this study, including its design and the procedure it follows.

Design. The DIT prototype introduced five automated systems to the participants though both visual- and auditory information (ACC, LC, OD, TS and RM). All visual information was displayed through an Augmented Reality (AR) overlay on the windscreen (Figure 8.1). The visuals mainly included symbols of specific functions and their capabilities and limitations. For example a symbol of a steering wheel with arrows to indicate that the Lane Keeping function is able to steer to keep the car within its lane. This type of Augmented Reality (AR) was used so the information could be directly related to the driving situation (Langlois & Soualmi, 2016), which may help drivers to interpret and apply the information (see Chapter 5). Additionally, by placing the visual information within the driver's direct field of view, as opposed to on a separate display in the car's dashboard, the gazes away from the centre of the road may be limited.

Several additional design choices were made in accordance with well-established ergonomic and safety guidelines for in-vehicle electronic devices to limit both the driver's visual- and mental workload, and the glances away from the centre of the road while effectively conveying the necessary information (summarized by: National Highway Traffic Safety Administration, 2013b;

Park & Im, 2020). First, all illustrations were placed as close to the centre of the road without blocking the driving situation. Second, the illustrations were semi-transparent (70% opacity) so the environment behind it was still visible to the driver. Additionally, no more than two illustration elements were present at the same time, and they did not include any written text.

Finally, all visual information was accompanied by verbal explanations for both redundancy and to be able to provide more detailed information. The standard digital Google Assistant voice was used for the verbal communication, and had been pre-recorded. This voice was female with a British accent. Please refer to Appendix D.3 for an overview of all visual- and verbal communication.

Figure 8.1. Examples of the Digital In-car Tutor visuals. a) Explanation of Lane Keeping. b) Explanation that the automation cannot deal with complex lane markings. c) Reminder that the automation had trouble driving in bad weather conditions.

Procedure. The DIT followed the following steps during Session 1 in the experiment. The DIT introduced one specific automated system (e.g. Adaptive Cruise Control) at the start of the scenarios. This was always on a straight road without traffic. The DIT would start by verbally explaining the functions, handling, equipment, capabilities and limitations of this system (Figures 8.1a and 8.1b). These were all supported by illustrations which were projected on the windscreen. The DIT would then stimulate participants to try out the automation. As participants approached the situation where they needed to either turn off the automation, or leave it on, the DIT would remind the participant of the system capabilities and limitations that applied to the specific situation (Figure 8.1c).

Adaptivity. The information from the DIT was expected to put some cognitive demand on drivers (Birrel, Young, Stanton, & Jennings, 2016; J. Rasmussen, 1983). To avoid overloading drivers, the length and type of DIT messages were adaptive to the complexity of the driving situation. This could be considered a ‘safety filter’ for our DIT as described by Van Gent et al. (2019). The communication was longer and more detailed in low complex situations, while it was condensed during highly complex situations. Furthermore, discussing theory and reflecting upon situations only occurred during low complex situations. This included the system introductions

on the simple straight road at the start of each scenario (Boelhauwer, van den Beukel, et al., 2020), and reflection after each critical situation. Action based instructions mainly occurred in highly complex situations. These strategies were based upon studies that investigated tutoring strategies by driving instructors (Boelhauwer, van den Beukel, Van Der Voort, & Martens, 2019a; Watson-Brown et al., 2018).

The DIT also adapted to the driving situation by reminding drivers of the system's capabilities and limitations specific to the current situation. In combination with the overlay visuals, this meant that the driver could directly perceive and process the information in their specific context. Drivers did not have to interpret information in an artificial context (e.g. a screen with a simplified visualisation of the situation) and then apply it to the current driving situation. For example when the weather changed for the worst in a scenario, the DIT reminded the driver that the car cannot function reliably in heavy fog and rain (Figure 8.1c).

Lastly, the DIT would adapt its feedback on the current performance of the driver. If the automation was used outside its Operational Design Domain (ODD), the DIT reflected afterwards why this was not safe. If the automation was unnecessarily turned off the DIT would also reflect on this. The DIT would add that the driver's judgement was the most important, and that the automation should only be used if the driver thought that it could safely cope. This feedback was manually activated by the researcher.

8.2.5 Set-up and procedure

The experiment was a between-subjects design with an experimental condition (DIT group) and a control group (IB group). Both groups drove in three sessions (Table 8.1), which each contained multiple scenarios. All participants were given the following task for each scenario: "You can start the scenario by driving manually. Turn on the automation whenever you think that the car can safely cope, and turn (or leave) it off if it cannot. The car can 'not cope' with a situation if: traffic regulations have to be violated or the car will damage something or harm someone."

At the start of Session 1, all participants received a written overview of the experiment procedure and filled out an informed consent form and the demographics questionnaire. Participants could get used to the simulator in a 10-minute demo scenario. Overall, session 1 consisted of 10 driving scenarios and lasted 1 hour. The DIT group received information and feedback from the DIT during all scenarios in session 1 (see 8.2.6 for a discussion of all scenarios), while the IB group read a brochure about the automation for 10 minutes before driving. Participants were reminded of their task before each scenario (mentioned above). Session 2 started after a 10-minute break. This session contained 8 test scenarios and lasted 30 minutes. Again, participants were reminded of their task before each scenario. The DIT was disengaged for all participants in this session.

Participants were selected upon availability to participate in Session 3, which took place two weeks after Session 2. The set-up for Session 3 was identical to that of Session 2.

Participants were informed at the start of each session that, while using the automation, they remained responsible for their safety and that of their fellow road users. They furthermore needed to adhere to the general traffic rules and speed limits. Last, participants were informed that the automation was specifically designed for this study and may not be the same as they experienced before in another car. If the participant hit something or someone, a crash sound was played and the scenario ended. After each scenario, participants were asked by the researcher whether they thought that the car could safely cope with the previous situation and why.

Table 8.1.
Overview of the experiment set-up for the Digital In-car Tutor (DIT) group and the Information Brochure (IB) group. Descriptions of all abbreviated driving scenarios are available in Table 8.2a and 8.2b.

		Session 1 (60 minutes, $N = 38$)										Session 2 (30 minutes, $N = 38$)								Session 3 (30 minutes, $N = 22$)							
IB group (control)	Info Brochure	Driving scenarios										Driving scenarios								Driving scenarios							
		ACC1	ACC2	LK1	LK2	OD1	OD2	TS1	TS2	RM1	RM2	T1	T2	T3	T4	T5	T6	T7	T8	T1	T2	T3	T4	T5	T6	T7	T8
DIT group		Driving scenarios + Tutor Guidance										Driving scenarios								Driving scenarios							
		ACC1	ACC2	LK1	LK2	OD1	OD2	TS1	TS2	RM1	RM2	T1	T2	T3	T4	T5	T6	T7	T8	T1	T2	T3	T4	T5	T6	T7	T8

8.2.6 Scenarios

All scenarios started with a straight road without traffic. This road was included so drivers could calmly start driving manually and turn on the automation if they thought that it was safe to do so. Furthermore, during session 1, the DIT introduced a new system to the DIT group on this road as they were still driving manually. After the straight road, the specific driving scenario started. All scenarios contained an event area during which the automation should be on or off.

Session 1 contained 10 driving scenarios (Table 8.2a) of 3 to 4 minutes each. Each of the five automated systems described in Section 8.2.2 had 2 dedicated scenarios that addressed a particular capability or limitation of that system. Each system contained 1 scenario in which the automation could cope, and 1 in which the automation could not. Session 2 and 3 both contained 8 test scenarios of 2 to 3 minutes each (Table 8.2b). In each session, 4 scenarios required a take-

over, and 4 did not. The scenarios in Session 3 were the same as those in Session 2 but with considerable changes to the environment. It made them look different to the participants, but still allowed for comparison with Session 2. If a participant did not take-back control in situations that the automation could not cope with, the car would crash and the scenario would end.

Table 8.2a.

An overview of all scenarios during session 1. Each scenario addresses a particular automated system (e.g. Adaptive Cruise Control).

Driving scenarios in Session 1			
ID	Scenario	Need to turn off the automation?	Description
ACC1	Straight highway	No	Straight highway without any traffic.
ACC2	Fog	Yes	Straight highway with fog coming up. Driver needs to turn off automation before the fog and brake for slow cars within the fog section. Car crashes if automation remains turned on.
LC1	Curved Rural	No	Curved rural road without any traffic.
LC2	Roadworks	Yes	Highway with roadworks. Driver needs to turn off the automation before the roadworks and follow the yellow road markings. Car crashes if automation remains turned on.
OD1	Jaywalker	No	City road with a pedestrian crossing the road
OD2	Pedestrian obstructed view	Yes	City road with a pedestrian crossing the road from behind a bus. Driver needs to turn off the automation when driving past the bus. Car crashes into the pedestrian if automation remains turned on.
TS1	Priority signs	No	Rural road and simple signalised intersection.
TS2	Unsignalised intersection	Yes	City road and intersection without traffic signs or lights. Poor view across intersection. Driver needs to turn off the automation before the intersection. Car crashes if automation remains turned on.
RM1	Pedestrian crossing	No	City road with pedestrian crossing on a zebra path.
RM2	Road markings missing	Yes	Highway with curved section without road markings. Driver needs to turn off automation before the section without road markings. Car crashes if automation remains turned on.

Table 8.2b.

An overview of all scenarios during session 2 and 3.

Driving scenarios in Sessions 2 & 3			
ID	Scenario	Need to turn off the automation?	Description
T1	Curved rural	No	Rural road with gentle curves.
T2	Stationary car	Yes	Rural road with broken down car in the middle of the road. Driver has to turn off automation when approaching and drive around the car. Car crashes if automation remains turned on.
T3	Emergency vehicle	Yes	Signalised intersections with emergency vehicles running the red light. The driver has to turn off the automation before the intersection. Car crashes if automation remains turned on.
T4	Jaywalker	No	City road with a pedestrian crossing the road.
T5	Obstructed view	Yes	City road with a pedestrian crossing the road from behind a large construction vehicle. Driver needs to turn off the automation before driving past the construction vehicle.
T6	Priority signs	No	Intersection with priority traffic signs and crossing traffic.
T7	Fog	Yes	Straight highway with fog coming up. Driver needs to turn off automation before the fog and brake for slow cars within the fog section. Car crashes if automation remains turned on.
T8	Highway traffic	No	Highway with gentle curves and several cars.

8.2.7 Variables

This study contained two independent variables: training method (DIT versus information brochure), and session (Session 1, 2 and 3). Three dependent variables were measured during the experiment: acceptance, appropriate automation use and take-over quality.

Acceptance. Participants in the DIT group indicated their acceptance of the DIT in a questionnaire at the end of the first session. This questionnaire was a slight adaptation of the Technology Acceptance Questionnaire (Park, 2009) and addressed 6 core aspects of technology acceptance: perceived ease of use, perceived usefulness, attitude, intention to use, self-efficacy, and social norm (Ajzen, 1991; Davis, 1989; Featherman, 2001; Venkatesh & Davis, 1996, 2000) (Appendix D.2).

Appropriate automation use. Each scenario contained an ‘event area’ during which the automation should be on or off. For events that required the automation to be off, the event area started at the latest moment the participant could turn off the automation and brake to avoid a crash. For example, when the participant was driving 100 km/h, the event area started 76 meters before the point where the car would crash into something or someone (members.home.nl/

johngrimbergen/remwegformule.htm). Scenarios in which the automation could be (left) on, the event area started after directly after the straight road at the start of the specific scenario. Whether a scenario required the automation to be off, was determined before the experiment, based on the system information used in the driver training. Four subcategories were used to specify the type of automation use during the event areas: 1) Appropriate take-over, the automation is off when necessary, 2) Appropriate reliance, the automation is on while it is safe, 3) Inappropriate take-over, the automation is off while this is not necessary, 4) Inappropriate reliance, the automation is on when this is not safe.

Take-over quality. In scenarios that required the automation to be (turned) off, three following take-over quality variables were measured from the moment the driver turned off the automation until the location of a possible collision: Time To Collision (TTC) (s), deceleration rate (m/s^2), and lateral acceleration (m/s^2) (Gold et al., 2016; Merat, Jamson, Lai, Daly, & Carsten, 2014).

8.2.8 Analysis

The data on ‘appropriate automation use’ was first analysed using a Chi-Square test. Next it was investigated how the ‘appropriate automation use’ evolved over time, for each of the training methods. This was achieved through a mixed model approach, specifically Generalized Estimating Equation model (GEE). A Generalized Estimating Equation model was created as: our study was a 2x2 repeated measures design, the independent variable was binary, and we wanted to control for variation between scenarios (Sainani, n.d.; Ziegler & Vens, 2010).

The average lateral acceleration and deceleration rates were determined for the scenarios that required a take-over, starting directly after the participant turned off the automation until the end of the scenario. Then, any group differences on ‘vehicle control’ were analysed through the use of unpaired independent t-tests.

8.3 Results

8.3.1 Appropriate automation use

Collisions. The total number of collisions appeared higher for the IB group in Session 1 ($N_{IB} = 24$, $N_{DIT} = 20$), Session 2 ($N_{IB} = 10$, $N_{DIT} = 5$) and Session 3 ($N_{IB} = 5$, $N_{DIT} = 1$). However, Chi-Square tests did not indicate significant differences in the individual sessions (all $p > .05$). Two specific scenarios showed a significantly higher number of collisions for the IB group on a .1 level. These scenarios were Obstacle Detection 2 (OD2) ($N_{IB} = 5$, $N_{DIT} = 1$, $\chi^2(1, N=38) = 3.167$, $p = .075$) and Traffic Signs 2 (TS2) ($N_{IB} = 3$, $N_{DIT} = 0$, $\chi^2(1, N=38) = 3.257$, $p = .071$).

Appropriate take-over and reliance behaviour. During the first session, the IB group used the automation more often inappropriately (either inappropriate reliance or inappropriate take-over) than the DIT group ($N_{IB} = 65$, $N_{DIT} = 46$)(Table 8.3). This difference was significant overall ($\chi^2(1, N = 379) = 4.285, p = .025$), and also for the specific scenarios OD2 ($\chi^2(1, N = 38) = 8.992, p = .003$) and RM2 ($\chi^2(1, N = 38) = 7.795, p = .006$). In the scenario OD2, a pedestrian crossed the street from behind a large bus that is blocking the view of the car's cameras. In RM2, the lane markings are missing just before a sharp curve. No significant differences were found in Session 2 ($N_{IB} = 32$, $N_{DIT} = 26$) ($\chi^2(1, N = 301) = .720, p = .240$) and Session 3 ($N_{IB} = 13$, $N_{DIT} = 17$) ($\chi^2(1, N = 176) = .643, p = .274$). The observed power was sufficient for the Chi-Square tests per session ($1-\beta > .8$, $d = .3$, $\alpha = .05$), but insufficient for between group comparisons in specific scenarios ($1-\beta < .6$, $d = .3$, $\alpha = .05$). Consequently, if we control for the number of scenarios through a rather conservative Bonferroni correction ($\alpha_{adjusted} = .05/26 = .002$), the differences found in individual scenarios are no longer significant (all $p > .002$).

Some specific scenarios appeared to show particularly more inappropriate automation uses compared to the other scenarios: ACC1 and T6. ACC1 ($N = 34$) was the very first scenario that any of the participants encountered during this study. T6 contained a signalized intersection with intersecting traffic ($N_{session2} = 20$, $N_{session2} = 10$). The car would stop for the crossing traffic through traffic signs and continue after all traffic had passed. Multiple participants indicated that they thought the buildings were too close to the intersection and might block the view of the cameras.

Next, a Generalized Estimating Equation procedure followed (2.3.7). The dependent variable was inappropriate automation use. The random effects were the participants and scenarios. The fixed effects were the groups and sessions (see Table 8.4). The chosen working correlation matrix type was 'exchangeable', as this resulted in the lowest Quasi Likelihood under Independence Model Criterion ($QIC = 917.230$) (Ziegler & Vens, 2010). The binary logit model showed a significant effect of session ($\chi^2(1, N = 856) = 17.158, p < .001$), but no overall effect of group ($\chi^2(1, N = 856) = .249, p = .618$), nor an overall interaction effect ($\chi^2(2, N = 856) = 4.186, p = .123$). However, there were near significant effects on a .05 significance level of group in session 1 ($\chi^2(1, N = 379) = 3.835, p = .050$) and session 2 ($\chi^2(1, N = 301) = 3.688, p = .055$).

Table 8.3.

Overview of overall inappropriate automation use (in counts) per scenario.

Session 1 ²	ACC1	ACC2	LK1	LK2	OD1	OD2 ²	RM1	RM2 ²	TS1	TS2	Total
IB group	16	2	3	2	7	12	5 ¹	10	6	1	64
DIT group	18	6	7	2	3	3	2	2	3	0	46
Total	34	8	10	4	10	15	8	12	9	1	110
Required take-over	N	Y	N	Y	N	Y	N	Y	N	Y	
Session 2	T1	T2	T3	T4	T5	T6	T7	T8	Total		
IB group	1	2 ¹	6	2	3	10	2	6	32		
DIT group	0	0	7	3	0	10 ¹	1	5	26		
Total	1	1	11	5	13	20	3	11	58		
Required take-over	N	Y	Y	N	Y	N	Y	N			
Session 3	T1	T2	T3	T4	T5	T6	T7	T8	Total		
IB group	0	1	3	2	2	4	0	1	13		
DIT group	1	0	2	3	0	6	0	5	17		
Total	1	1	5	5	2	10	0	6	30		
Required take-over	N	Y	Y	N	Y	N	Y	N			

¹ = 1 missing participant. ² = Significant difference between groups on .05 level.

Table 8.4.

Generalized Estimating Equations model for appropriate automation use. The working correlation matrix was exchangeable. The random effects were the participants and scenarios. The fixed effects were the groups and sessions.

Parameter	β	95% CI	SE	p
Intercept	1.375	1.016 - 1.735	.183	.000
IB group	.369	-.447 - 1.185	.416	.375
Session1	-.234	-.727 - .259	.252	.352
Session 2	.190	-.173 - .553	.185	.306
IB group * Session 1	-.840	-1.681 - .001	.429	.050
IB group * Session 2	-.621	-1.255 - .013	.324	.055

Note. The DIT group and Session 3 statistics are not included as these were the baseline.

Looking at the specific types of inappropriate automation use (inappropriate take-over or inappropriate reliance), it appeared that the IB group had more inappropriate reliance decisions

in session 1 ($N_{IB} = 27$, $N_{DIT} = 13$), session 2 ($N_{IB} = 16$, $N_{DIT} = 12$) and session 3 ($N_{IB} = 6$, $N_{DIT} = 2$) (Figure 8.2). Analysis only confirmed a difference between groups in inappropriate reliance decisions for sessions 1 ($\chi^2(1, N = 190) = 6.20$, $p = .020$). DIT group had more inappropriate take-overs in session 3 ($N_{IB} = 7$, $N_{DIT} = 15$) ($\chi^2(1, N = 88) = 3.879$, $p = .049$) in session 3. That is, they did not rely on the car when it was safe to do so more often than the IB group. The observed power for these Chi-Square tests was sufficient at $> .8$ ($d = .3$, $\alpha = .05$).

Figure 8.2. Overview of the different types of (in)appropriate automation use. Inappropriate take-over means that the driver unnecessarily turned off the automation. Inappropriate reliance indicates that the automation was on when it was not safe.

Overall, the DIT group appeared to have more appropriate automation use than the IB group during session 1 and 2. However, a significant difference was only confirmed for session 1. Considering the specific types of automation use, the DIT group consistently showed less inappropriate reliance behaviour than the IB group throughout all sessions. These differences were significant for session 1, but not for session 2 and 3. Surprisingly, the DIT group unnecessarily took back control (inappropriate take-over) more often than the IB group in session 3.

8.3.2 Take-over quality and vehicle control

During the first driving session, the DIT group showed larger Times To Collision (TTC) at take-over in three (ACC2, OD2 and RM2) out of five scenarios that required a take-over (Figure 8.3). For the scenario ACC2, the DIT group took back control significantly earlier ($M_{DIT} = 11.30$, $SD_{DIT} = 7.54$) than the IB group ($M_{IB} = 3.48$, $SD_{IB} = 3.57$) ($t(20.59) = 3.80$, $p = .001$). The DIT group also took back control significantly earlier in the scenario OD2 ($t(27) = 2.45$, $p = .025$), with a

mean TTC of 6.19 seconds for the DIT group ($SD = 2.55$) and 3.67 seconds for the IB group ($SD = 2.92$). Similarly, the DIT group took back control significantly earlier in scenario RM2 ($t(21.63) = 2.27, p = .034$). In this scenario, the mean take-over distance was even negative for IB group indicating take-over after the collision location has already past ($M_{IB} = -0.03, SD_{IB} = 2.12$) ($M_{DIT} = 1.24, SD_{DIT} = .93$). In session 2 and 3, it still appeared that the IB group took back control later in most scenarios that require a take-over, however these results were not significant.

Figure 8.3. TTC when participants took back control.

During Session 1, the deceleration rate (m/s^2) was higher for the IB group in the same three scenarios in which the IB group showed later take-overs (ACC2, OD2 and RM2) (Figure 8.4). In scenarios ACC2 ($M_{IB} = 1.79, SD_{IB} = .79, M_{DIT} = .88, SD_{DIT} = .44$) ($t(34) = 4.12, p < .001$) and RM2 ($M_{IB} = .83, SD_{IB} = .38, M_{DIT} = .61, SD_{DIT} = .23$) ($t(34) = 2.10, p = .043$) the IB group decelerated significantly faster. This was also the case in scenario OD2, but only on a .1 significance level ($M_{IB} = 2.25, SD_{IB} = 2.89, M_{DIT} = .92, SD_{DIT} = .61$) ($t(28) = 1.85, p = .075$). During the second session, only scenario Test 6, showed difference between groups on deceleration rate on a .1 significance level ($M_{DIT} = .68, SD_{DIT} = 1.97, M_{IB} = .89, SD_{IB} = 2.51$) ($t(36) = 1.72, p = .093$). None of the scenarios in session 3 showed significant differences on deceleration rate between groups.

In session 1 and 2, none of the scenarios showed a significant difference between groups on the average lateral acceleration after take-over. In session 3, only one scenario (Test 9) showed a significant difference between groups on the average lateral acceleration after take-over ($t(19) = -2.38, p = .028$). In this particular scenario, the DIT group showed a higher average lateral acceleration ($M_{DIT} = .57, SD_{DIT} = .18, M_{IB} = .36, SD_{IB} = .22$).

Overall, the DIT group showed significantly larger TTCs, and smaller deceleration rates during the first session. This indicates earlier and consequently more gentle take-overs by the DIT group. While this still appeared to be the case in session 2 and 3, the differences were no longer significant. Only one scenario across all sessions showed a difference between groups in lateral acceleration. In this case, the DIT group showed a larger lateral acceleration. The possibility of Type II errors needs to be taken into account for the take-over quality and vehicle control variables, as the power was $< .8$ for these tests ($d = .5, \alpha = .05$) (Cohen, 1992).

Figure 8.4. Deceleration rate after the participants took back control. * = significant on a .05 level. ** = significant on a .1 level. The error bars represent the Standard Error.

8.3.3 Acceptance

At the end of first session, participants in the DIT group rated their agreement to several statements about the DIT on a scale of 1 (Strongly disagree) to 7 (Strongly agree) (Figure 8.5). Overall, the participants agreed that the DIT was easy to use ($M = 5.79, SD = .93, 95\% CI = 5.34-6.24$), and useful ($M = 5.72, SD = 1.18, 95\% CI = 5.15-6.29$). Participants were positive towards the DIT ($M = 5.74, SD = 1.11, 95\% CI = 5.20-6.27$), and disagreed that it was annoying or frustrating ($M = 2.63, SD = 1.28, 95\% CI = 2.02-3.25$). Furthermore, the large majority of participants ($N = 32$)

showed intent to use the DIT if it was in their partially automated car ($M = 5.05$, $SD = 1.65$, 95% $CI = 4.26-5.85$), and felt that they were capable in using it ($M = 5.87$, $SD = 0.47$, 95% $CI = 5.64-6.09$). Participants disagreed that people who are important to them think that they should use the DIT ($M = 3.79$, $SD = 2.12$, 95% $CI = 2.77-4.81$). This seems logical as their friends and family do not know about the DIT.

Figure 8.5. Overview of the acceptance ratings by the DIT group. The error bars indicate the 95% Confidence Intervals.

8.4 Discussion and conclusions

In this study, we evaluated a Digital In-car Tutor (DIT) prototype for a complex (simulated) partially automated car. It was hypothesized that the prototype would support drivers in deciding when it is safe to use the automation, and consequently lead to better vehicle control when taking back control. To study this, we compared appropriate automation use and take-over quality, between two groups over three driving sessions. The control group received information about the car automation through a brochure (IB group), while the experimental group received the information from the DIT prototype during the first driving session (DIT group). Drivers were instructed to turn on the automation whenever they thought that the car could safely cope with the situation, and turn (or leave) it off if it could not. Each scenario contained an event in which it was either safe or unsafe to use the automation. This way, the automation use could be classified as follows: 1) Appropriate take-over, the automation is off when necessary, 2) Appropriate reliance,

the automation is on while it is safe, 3) Inappropriate take-over, the automation is off while this is not necessary, 4) Inappropriate reliance, the automation is on when this is not safe.

8.4.1 Appropriate automation use

During the first driving session, the DIT group showed overall more appropriate automation use compared to the IB group. This suggests that the DIT was more effective in supporting drivers to safely learn about, and try out, the automated functions of the car compared to reading the brochure. During the second session, in which the DIT was no longer active, this still appeared to be the case but the difference was no longer significant. During the third session, the two groups showed a similar level of appropriate automation use. Although most learning is believed to occur during the initial interaction (Beggiato, 2014; Beggiato, Pereira, et al., 2015; Forster, Hergeth, Naujoks, Beggiato, et al., 2019), it may still be necessary to increase the duration (and number of situations) in which the DIT is active to obtain a higher final performance level. Especially as multiple studies, like those by Beggiato (2014; 2015) and Forster (2019), have shown that the learning curve stabilizes after approximately five interactions (or 3,5 hours). Extended DIT support may also be necessary as situations that have not been experienced for a long time can fade from the driver's mental model (Beggiato, Pereira, et al., 2015). Longer (but not necessarily continuous) DIT support also provides the option to highlight rare situations.

8.4.2 Inappropriate automation use

The DIT group already showed less inappropriate reliance during the first session, compared to the IB group. By the third session, the amount of inappropriate reliances of the DIT group had further decreased to around two and a half percent of all interactions. While the IB group also showed a decrease in inappropriate reliances over time, both the initial and final amount of inappropriate reliances appeared to be higher compared to the DIT group. During the third session, the brochure group still showed around seven percent of inappropriate reliances of all interactions. These results follow our expectations based on both established and more recent models that describe the interaction between automation feedback and automation use (Lee & See, 2004; Revell & Bradley, 2020; Seppelt, 2009; Seppelt & Lee, 2019). All these interaction models include the notions that (external) information about the automation, as well as repeated interactions, and automation feedback all affect automation use (and reliance). The results suggest that by combining all these elements in the DIT, it was effective in specifically decreasing inappropriate reliance behaviour. This is an important implication of the prototype as inappropriate reliance can lead to severe safety issues.

Both groups had a similar amount of unnecessary take-overs during the first driving session. While the amount of unnecessary take-overs decreased over time for the IB group, it appeared

that this was not the case for the DIT group. It seems that the DIT group was more careful to rely on the automation throughout the driving sessions. These results are unexpected as they are not in line with the statement that repeated interactions, feedback and background information lead to improved mental models and consequently appropriate automation use. One explanation could be that the repeated information and feedback by the DIT stressed the limitations of the automation. The limitations were discussed repeatedly to explain the present situation, and may have made the drivers less trusting towards the automation. It is important to realize that unnecessary take-overs are not necessarily dangerous, and arguably preferred in ambiguous situations. Still unnecessary take-overs need to be limited so the automation can be used to its full potential. If drivers are constantly disengaging the automation when it is unnecessary, potential benefits of the automation such as increased traffic safety and driver comfort may not be achieved.

Two particular driving situations were very difficult for both groups: ACC1 and T6. It was safe to leave on the automation in both situations. ACC1 was the very first scenario that all drivers encountered during the study. During this scenario, the car was driving automated on the highway and approached slightly slower preceding vehicles. The car would automatically slow down to keep a set distance to the cars. It was therefore not necessary for the driver to take back control. As discussed earlier, drivers need repeated experience and feedback to develop a calibrated level of trust (Beggiato, Pereira, et al., 2015; Forster, Hergeth, Naujoks, Beggiato, et al., 2019; Walker et al., 2018). While reassurance feedback may support a higher initial level of trust, a DIT should never suggest that the automation can perfectly handle a situation. Scenario T6 was a signalized intersection with crossing traffic. The automated car would detect the priority signs and stop to let the crossing cars pass. Drivers did not rely on the car as they thought that the houses were too close to the street and might block the view of the car's cameras. This suggests that the drivers were well aware of the limitations (blocked cameras) and capabilities (detecting priority signs) of the automation. However, as no specific camera ranges were provided during the training this particular situation became ambiguous for the drivers. Taking back control was then arguably the safest decision.

8.4.3 Take-over quality and DIT acceptance

We expected to see better vehicle control for the DIT group after disengaging the automation in situations that required to take back control (Gold, Damböck, Lorenz, et al., 2013; Rudin-Brown & Parker, 2004). The DIT group took back control significantly earlier, and braked less hard, than the IB group during the first session. No significant differences were found between the groups in the second and third session. Still, the minimum Time To Collision at take-over was consistently larger, and the maximum deceleration smaller, for the DIT group. While overall no differences between groups were found for the lateral acceleration after take-over, one scenario surprisingly

showed a larger lateral acceleration for the DIT group. The possibility for Type II errors need to be taken into consideration for the vehicle control variables as these tests had limited power.

Our results show that participants found the DIT easy to use. Participants also indicated that the DIT made learning about, and using, the automation easier. They felt positively about the DIT, and confident in using it. Participants indicated an intent to use the DIT, but did not think that their peers and family felt that they should use it.

8.4.4 Limitations

Certain limitations concerning this study have to be taken into account. First, participants in the control group were asked to read the brochure carefully before entering the driving simulator. However, in real life a large share of drivers does not read the owner's manual, nor looks up any other information about the automation in their car (Boelhouwer, et al., 2020; Harms & Dekker, 2017). Therefore, the group will not be representative of all drivers. A brochure was chosen for the control group as this is often used by car sellers as the main (and only) method of providing customers with information about the automation in their new car (Boelhouwer, et al., 2020). An additional study with a control group, that does not receive any information about the automation before driving, may be required for improved representation of current drivers.

Second, participants could only turn off the automation by pressing a button on the steering wheel. It is possible that the inability to disengage the automation through the brake has caused confusion among drivers in time critical situations. However, participants were reminded that they had to disengage the automation through the button, and not the pedals, multiple times throughout the driving sessions.

Last, the current between-subject set-up did not allow us to compare the acceptance between the DIT and an information brochure. Additional studies with a within-subject design are required to examine the acceptance of the DIT more extensively.

8.4.5 Future research

The results of this study provide multiple opportunities for further research. In order to evaluate the concept of a DIT it was necessary to develop a practical prototype. As the exact design parameters of a prototype (e.g. size, placement, symbols) will always contribute to the level of its effectiveness, it is necessary to investigate a wide variety of DIT designs and their effects on automation use. Additionally, the effects of a DIT on driver distraction need to be assessed. By projecting the transparent images on the windscreen, the driver does not have to continuously shift his attention from the road to a secondary screen. However, the images are still expected

to introduce glances away from the centre of the road and take-up cognitive resources. They therefore need to be further refined so they facilitate optimal learning while limiting distraction from the road. To adhere to the NHTSA guidelines on the number and duration of glances away from the centre of the road (National Highway Traffic Safety Administration, 2013b, 2016), the images may need to be, for example, located closer to the centre of the driver's field of view without causing visual clutter (Kroon et al., 2016; Stevens, Quimby, Board, Kersloot, & Burns, 2002). Finally, while the concept prototype used the entire windscreen to project the images on, more practical implementations need to be explored. For example, the DIT may be implemented in an off-the-shelf head-up display device.

8.4.6 Conclusions

Overall, the Digital In-car Tutor (DIT) prototype showed promising results in guiding drivers to safely use a partially automated car. Use of the DIT overall lead to more appropriate automation use and higher quality take-overs. These effects of the DIT were predominantly found within the first driving session, as the DIT was active, but came to the same level in both groups by the last driving session. Still, use of the DIT specifically lead to less inappropriate reliance behaviour throughout the driving sessions. That means that drivers relied less on the automation in situations that were outside of its Operational Design Domain. Therefore, a DIT may support traffic safety by reducing overreliance. The results further indicated a possible under-trust of the automation among users of the DIT. It is necessary to investigate how to address this under-trust without the risk of creating overreliance. Finally, drivers found the DIT easy to use, useful, and felt confident in using it. A DIT shows potential as an effective solution, towards safe guided learning in partially automated cars.

Part IV Reflection

Chapter 9

Discussion of main findings and conclusions

Chapter 9. Discussion of main findings and conclusions

Although automated driving may provide many benefits for traffic safety and driver comfort, appropriate automation use⁷ is necessary for these benefits to emerge. Even more so, inappropriate automation use may actually negatively impact traffic safety. To be able to supervise and appropriately use the automation, drivers need to have an accurate understanding of its functionalities and limitations. However, learning how and when to use the automation is very difficult for drivers due to the complexity of current partially automated cars, and the vast amount of unique driving scenarios that can be encountered. Drivers need to be supported in understanding and appropriately using their cars' automation. The goal of this thesis therefore has been to *explore, design and validate an in-car HMI to support drivers in understanding and appropriately using car automation*. To reach this goal, the following research questions were investigated throughout this thesis (see also Section 1.1):

- 1) How are drivers currently supported in understanding and appropriately using car automation?*
- 2) How may current driver support be improved to aid understanding and appropriate use of car automation?*
- 3) What tutoring strategies do driving instructors employ, and (how) are these adaptive to driving situations and students?*
- 4) How can the design of a Digital In-car Tutor learn from the driver support strategies determined in research questions 2 and 3?*
- 5) How does use of a digital in-car tutor affect automation use?*

This chapter presents the main contributions of this thesis regarding these questions. Section 9.1 discusses the main findings of this thesis. Next, Section 9.2 provides recommendations for further research. Finally, Section 9.3 closes the chapter with the final conclusions of this thesis.

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Appropriate automation use refers to using the automation when it is safe and driving manually when the automation cannot cope. See Section 2.5 for a discussion of appropriate automation use.

9.1 Discussion of main findings

9.1.1 Issues with current driver information

Research question 1: How are drivers currently supported in understanding and appropriately using car automation?

This thesis started with an evaluation of the way that drivers are currently supported in understanding and using their car's automated functions. This evaluation commenced with nation-wide surveys among drivers and car sellers. Next, a simulator study was conducted to assess whether (and how) the most common ways that drivers learn about their car automation (i.e. through trial-and-error or the owner's manual) support appropriate automation use. Furthermore, the HMI of currently available cars were reviewed. The results of these studies together lead us to conclude that drivers are insufficiently supported in creating an accurate understanding of their car's automation. This hampers appropriate automation use. In this section, we will discuss the main issues of the ways that drivers are currently informed about the automation in their car.

Our surveys among drivers and car sellers (Chapter 3) showed that one of the main issues with the way that drivers are informed about their car automation is the lack of complete, accurate and understandable pre-drive information (i.e. information that drivers receive or look up before driving). Almost a quarter of all drivers leaves their car dealers without any explanation on the automation in their new car. Moreover, information that *is* provided most of the time does not include the automation's capabilities and limitations. This is highly troublesome as all currently commercially available partially automated cars require the driver to decide when it is (not) safe to use it. Additionally, only very few drivers are able to try out the automation at the dealership or receive an official training. The lack of information for drivers can, at least partially, be attributed to the way that car sellers are trained. We found that almost forty percent of car sellers does not receive sufficient information about car automation (e.g. from the manufacturer or wholesaler). This is especially the case for independent car dealers. Additionally, car sellers indicate that they lack sufficient time and resources to provide drivers with basic automation information.

The results of our survey study show that the lack of complete information leads to drivers mainly learning about their car's automation through the owner's manual and sales brochures. Additionally, drivers that do not receive any information from their dealer and do not actively search for information themselves have to rely on trial-and-error. This will even be the case for novice drivers as the majority of current driving schools do not include car automation in their practical education program. While these findings are in line with other recent survey studies like those by Abraham et al., (2018) and Harms, Bingen, and Steffens (2020), we found that

both these learning methods (i.e. reading the owner's manual and trial-and-error) pose severe safety issues. First of all, our driving simulator study in Chapter 4 showed that solely reading theoretical information about the automation beforehand is insufficient to support appropriate automation use. Drivers that received information beforehand did not use the automation more appropriately than those who did not receive the information. The recent studies by Noble, Klauer, Doerzaph, and Manser (2019) and Mueller, Cicchino, Singer, and Jenness (2020) further confirm these results. While reading an owner's manual did result in accurate inert knowledge⁸ about the automation in our study, actually applying the information in dynamic driving situations and determining the appropriate reliance action remained difficult. As manuals cannot cover all possible scenarios, they provide general information that needs to be transferred to individual situations (Loggem, 2013). The transfer of knowledge is expected to place high cognitive demands on the driver, especially considering the complexity and variety of driving situations. Finally, it is highly impractical to provide updated manuals after each over-the-air car update and expect drivers to re-read it before using the automation (especially if this has no significantly positive effect on automation use). Regarding learning by trial-and-error, we conclude that this is overall a dangerous and incomplete way of learning about car automation. Our second driving simulator study compared automation use between drivers that solely learned through trial-and-error, and drivers that both received theory *and* could practise (through a Digital In-car Tutor) (Chapter 8). Drivers which solely learned through trial-and-error required more interactions to come to a similar level of appropriate automation use as drivers that received theory *and* could practise. Even more importantly, after multiple separate driving sessions they still relied more on the automation when it was unsafe to do so. Learning solely through trial-and-error puts traffic safety at risk as the unguided learning process, which includes making errors, takes place on the road. Additionally, with trial-and-error the entire learning process takes place without reflective feedback. That is, drivers do not receive explicit feedback why the automation performed a certain way, and whether (and why) their automation use was (in)appropriate.⁹ Instead, they have to rely on cues from the automations driving behaviour and the driving environment to create an understanding about the automation. As learning through trial-and-error is extremely limited to the specific scenarios that are encountered, drivers have to extend their assumptions based on comparable prior situations to infer the required action (i.e. taking over or not). Considering the complexity and variability of both driving situations and current automated car functions, drivers will make incorrect or overly generalised assumptions about the automation and consequently use the automation inappropriately. Indeed, this has already been identified as an important factor in recent car accidents (Onderzoeksraad voor Veiligheid, 2019).

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8 See also Sarter et al., (1997)

9 Current HMI do not provide these types of information, see Chapter 5.

An additional issue is the lack of a centralized, model specific, updated and reliable information source. The information should be model (and update-) specific as both the names and functionalities of automated function vary largely across car brands (Abraham, Seppelt, et al., 2017; Teoh, 2020). This is not only important for drivers that buy a new car, but also in the context of car sharing. However, current owner manuals are often not specific to the exact model and included automation, especially as most new cars are highly customizable. Furthermore, they don't include information about the latest automation updates. Consequently, our surveys among drivers and car sellers indicate that they resort to searching for information on various websites including web forums and video-sharing websites such as YouTube (Chapter 3). Although these may be helpful, the information on these websites may be inaccurate or incomplete as it is not validated by either the corresponding car company or a regulatory organization. Even in centralised attempts to information provision (e.g. by the US National Safety Council), the provided information is not model- or brand specific.

In conclusion, drivers are currently insufficiently supported in learning about the automation in their car. Underlying reasons are the lack of (thorough) information and training, as well as a lack of a centralized place for drivers to look up model- and update specific information. All these issues contribute to inappropriate and unsafe automation use. We need to be more critical on whether it is ethical and desirable to have partially automated car systems on the market without a thorough support system in place. Generally one would not allow an untrained new employee to use a highly complex machine in a factory without any help. Yet this is happening with partially automated cars, but in a high risk and dynamic environment with other (vulnerable) road users. It is necessary to take action and make sure that drivers are better supported in understanding and appropriately using their car's automation. The following section therefore provides several insights for improved driver support that were obtained through the studies in this thesis.

9.1.2 Lessons learned on in-car driver support

Research question 2: How may current driver support be improved to aid understanding and appropriate use of car automation?

Research question 3: What tutoring strategies do driving instructors employ, and (how) are these adaptive to driving situations and students?

The above two research questions will be answered together in this section. Considering the identified issues with current driver information (Section 9.1.1) we conclude that it is necessary to specifically develop an in-car HMI to aid drivers in understanding and appropriately using their partially automated cars. By including the support in the car itself, all drivers receive information about their car's automation. This support is provided even if they didn't receive any external

information or training, nor actively looked for information themselves. Additionally, drivers can be informed and supported for a longer period of time, in contrast to one time training at a driving school or in a simulator. Finally, any provided information can be model specific and updated after any over-the-air updates to the automation.

Throughout this thesis we determined several aspects that should be included in such an in-car HMI, that aims to support driver's understanding and appropriate use of the automation. First of all, the HMI should combine theory and practice. More specifically, it should provide basic information of the specific automated functions within the car, paying careful attention to the automation's capabilities and limitations and the driver's new role, and allow the driver to practise using the automation. As discussed in Section 9.1.1, our simulator studies (Chapters 4 and 8) have shown that solely learning through theoretical information before driving or by trial-and-error is insufficient. However, our second driving simulator study showed that the combination of theory and practice (through a Digital In-car Tutor) does have a positive effect on appropriate automation use at an early stage (Chapter 8). Several other recent studies confirm these findings as they indicate a positive effect of interactive training (combining theory and practice) on: understanding of the automation, appropriate automation use, and take-over quality (Ebnali et al., 2019; Ebnali, Lamb, & Fathi, 2021; Forster, Hergeth, Naujoks, Krems, et al., 2019; Payre et al., 2017; Sportillo, Paljic, & Ojeda, 2019). We therefore conclude that an in-car HMI should provide both information on the car's automated functions as well as guided practice of the automation. Second, the information of the HMI should be directly related and adaptive to the current driving situation to support understanding and appropriate use of the automation. In Chapter 5, we reviewed the HMI of both commercially available partially automated cars, and those of car concepts in literature. This review revealed that current HMI generally only provide very basic information on the automation state that is unrelated to the exact situation at hand (i.e. on or off). They do not provide the driver with specific information on what the automation is doing¹⁰. Additionally, they do not inform the driver why the automation is (capable of) performing this action. This makes it difficult for drivers to learn what the automation can do, under which circumstances, and why. Especially during the initial use period, it is necessary to provide information about the automation's actions in direct relation to the current driving situation to allow drivers to form an accurate understanding (e.g. why can the automation function in the current situation, see also Koo et al., (2015)). To gain insights in whether and how an HMI should practically be adaptive to the driving environment, we explored existing feedback strategies among driving instructors in an observation study (Chapter 6). Additionally, we investigated how the information should be adaptive to the complexity of the driving situation as literature has suggested to adapt the information of the HMI to the *complexity* of the driving environment as this complexity can highly affect drivers' workload and ability to comprehend

the provided information (Gold et al., 2016; Lyu et al., 2017; Radlmayr et al., 2014). From this observation study, we conclude that specifically the feedback/information length, level of detail and content type should be adaptive to the complexity of the driving environment to stimulate situated learning while avoiding overloading the driver. When the driving situation becomes more complex, the length and level of detail of information should be reduced. Elaborate explanations (e.g. an explanation on the general functions of the automation), and reflective feedback (e.g. feedback on the driver's take-over decision) should be limited to situations of low complexity, while highly complex situations should mainly include action based information.

In order to be able to conduct this study, and examine how an HMI may need to be adaptive to the *complexity* of the driving situation, it was necessary to first determine what elements actually contribute to the overall complexity of a driving situation. A combination of online surveys and a literature review were used to investigate this (Chapter 7). From that study, we conclude that while both infrastructure and traffic contribute to the perceived complexity of driving scenarios, traffic elements have a larger influence. Additionally, by combining infrastructure- and traffic elements the perceived complexity of driving situations further increases. Infrastructural elements that increase the perceived complexity are for example: sharp turns, slopes, obstacles, road narrowing and unfamiliar constructions. Traffic elements that increase the perceived complexity include: traffic density, varying road user types and multiple travel directions of other road users.

Finally, the HMI needs to be adaptive to the driver's experience. Through our observation study among driving instructors and student drivers (Chapter 6), we found that the information needs of student drivers change as they gain experience. We envision a similar trend as drivers gain experience with the automation in their car. Especially during the initial use period, drivers require elaborate information to form a basic understanding of the automation. This includes general information about the automation itself (i.e. its functionalities, handling and capabilities and limitations), but also about the driver's new role, and any HMI elements (e.g. symbols). Additionally, drivers without experience with the automation need more detailed information on why the automation is (capable of) performing a certain action. Finally, repetition and practice of all this information needs to be more frequent during the first use period. As drivers gain experience, it may no longer be necessary or even considered to be annoying to frequently repeat the information. However, rare yet critical limitations and situations will still need to be occasionally addressed as these can be easily forgotten if they are not experienced (Beggiano & Krems, 2013). In conclusion, the HMI of partially automated cars not only need to be adaptive to the driving environment, but also to the experience of the driver in order to support accurate understanding and appropriate use of the automation¹¹.

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¹¹ While outside the scope of this thesis, the HMI similarly needs to adapt to other driver characteristics to support appropriate automation use such as the driver's trust or affinity with technology.

9.1.3 A Digital In-Car Tutor for driver support

Research question 4: How can the design of a Digital In-car Tutor learn from the driver support strategies determined in research questions 2 and 3?

The key insights obtained through our surveys, observational study and simulator studies (as described in the previous sections) were used to develop and evaluate a Digital In-car Tutor (DIT). This DIT aims to support drivers in learning about, and appropriately using, the automation in their car. A key unique characteristic of the developed DIT is that it provides guided learning about, and practice of, the car automation during regular trips¹². It introduces a new automated function (e.g. Adaptive Cruise Control) (including the handling, capabilities and limitations) on simple roads without traffic, after which the driver is guided in trying out the function. Additionally, it provides reminders of specific limitations if a relevant situation is encountered. This section describes how our DIT includes the strategies from Section 9.1.2, and how it affects automation use.

First, it provides every driver with basic information about the automation's functions, capabilities, limitations and handling during regular driving trips. Second, the DIT includes both theoretical information and on-road practice, and provides a stepwise approach by only offering functions if others have already been practised. Third, the DIT can be adaptive to the current driving situation and the driver's experience. The automated functions are explained within their relevant driving scenarios to stimulate situated learning. In highly complex situations, the information is reduced in length and detail to avoid cognitive overload. Additionally, the information is more elaborate and reflective (both on the automation's and driver's actions) in situations of low complexity and for drivers with little automation experience. Fourth, a DIT allows for long-term support in learning (when and how) to use the automation. This includes occasional reminders of rarely occurring but important system limitations to avoid that this information is forgotten. Finally, any information can be model specific and updated if functions are changed through an over-the-air update.

Research question 5: How does use of a Digital In-car Tutor affect automation use?

Based on the results of all previously conducted studies, we developed a DIT prototype in our driving simulator and evaluated its effects on drivers' automation use (Chapter 8). This prototype gradually guided drivers in learning about, and practising with, the car's (simulated) automated functions. From this study, we conclude that our DIT indeed positively affects appropriate automation use and quality of take-overs during the first period of automation use. More specifically, during the first driving session, drivers with the DIT were more likely to use the

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See Section 8.2 for an extensive description of our Digital In-car Tutor prototype.

automation when it was safe to do so, and decide to drive manually in situation outside the automation's capabilities. While the behaviour of drivers without a DIT eventually converged to a similar level of appropriate automation use, it is crucial for traffic safety that drivers already show appropriate automation use and high quality take-over behaviour during the first on-road drives. Furthermore, drivers that received our DIT specifically show less inappropriate reliance behaviour throughout the driving sessions. This means that drivers were less likely to rely on the automation in situations where it was not safe to do so, which is especially important for traffic safety. Still, it must be noted that even though users of the DIT showed more appropriate automation use than drivers without the DIT, there was still a percentage of drivers that falsely relied on the automation throughout the driving sessions. While the studies by Ebnali et al., (2019 and 2020) found similar effects of (VR) simulator training on understanding automation use, simulator training misses many of the previously discussed DIT benefits (e.g. long-term support). Overall, we conclude that the concept of a DIT shows potential in efficiently supporting drivers in appropriately using automated car functions at initial use.

9.2 Recommendations for future research

This thesis clearly shows that drivers are currently insufficiently informed about the automation in their car, and a new approach is necessary to properly support them in understanding and using the automation. Our studies indicate that a Digital In-car Tutor (DIT) shows potential as an efficient and effective way for drivers to learn about their car's automation and to foster appropriate automation use. However, before an actual DIT can be implemented within a real driving context more research is necessary. Additionally, as every study, this research had to be performed within certain limitations. The current section will discuss these limitations and provide recommendations on how these may be addressed in future research. Finally, this section highlights the main opportunities for further research and development of a DIT.

9.2.1 Study limitations

Several limitations with regard to this dissertation's studies should be taken into account. While our driving simulator study in Chapter 4 (which investigated the effects of written information before driving on automation use) included repeated measures and provided many data points per participant, it is still possible that no differences were found between groups due to the smaller sample size of this study. Additionally, the set-up of this study did not allow us to record the quality of take-over behaviour (e.g. take-over time or lane deviation) as video recordings were used in this study instead of simulator software.

Next, in order to evaluate the concept of a Digital In-Car Tutor (DIT) in Chapter 8, it was necessary to develop a practical prototype. While the design of this prototype was carefully developed based on both the results of our own studies and general human factors guidelines, we recognize that the specific design parameters of the prototype will always contribute to its effects. These include for example the specific symbols that are used and their size and placement. The results of our study are therefore directly related to this particular design. It is therefore crucial to extend this study and evaluate a wide variety of designs and their effect on automation use.

Additionally, the results of our DIT evaluation (Chapter 8) suggest that there is a risk that a DIT leads to lowered trust and consequently underreliance (i.e. unnecessary take-overs) because of pointing out the automation's limitations. This is in contradiction with studies that indicate that trust is not (or less) affected after system failure if drivers are aware of its limitations beforehand (Beggiato & Krems, 2013). It may be that repetition of the automation's limitations causes drivers to overgeneralize them, or infer that these are more frequent than they actually are. Further research is necessary to be able to provide drivers with sufficient knowledge about the automation's limitations without causing under-trust.

Finally, we investigated tutor strategies of driving instructors (in Chapter 6) and used these as inspiration for our DIT prototype (in Chapter 8). However, individual driving instructors have different tutor styles. Not all of these may be optimal to stimulate learning. Moreover, individual drivers may have different tutor style preferences. For example, a very anxious driver may need a more gentle and reassuring tutoring style. Therefore, the tutor style used in our DIT prototype may not work for all drivers. While this research did not investigate individual preferences for different tutor styles, it is advised to include these topics in further DIT research to foster an optimal learning environment.

9.2.2 Future research and development of an adaptive Digital In-car Tutor

In this thesis, we developed a first prototype for an adaptive Digital In-car Tutor (DIT) which was evaluated in a driving simulator study. This DIT shows promise to support drivers in understanding and appropriately using the automation in their cars. Still there are some important research opportunities to advance the knowledge, development and practical implementation of DITs which we will discuss in this section.

The developed DIT already aims to limit the cognitive load by adapting its information to the complexity of the driving situation (see also Section 8.2.4). Additionally, the visuals on the windscreen are placed close to the centre of the road to avoid long glances away from the road. Still, as the visuals and audio require attention from the driver we suggest to follow up our study by investigating whether drivers are still capable of quickly and safely responding to

emergencies while the DIT is actively explaining a function (to a similar extent as drivers without the DIT). Several studies have indicated that engagement in visual- and auditory secondary tasks negatively affect take-over times and take-over quality in emergencies (Wandtner, Schömig, & Schmidt, 2018; Zeeb et al., 2016). Particularly the visual elements of the DIT may cause visual or cognitive distraction as they require the driver to look away from the centre of the road. It should be investigated how a specific DIT design affects drivers' gaze patterns, cognitive load and response time and quality. While general recommendations for head-up display visuals have been studied (National Highway Traffic Safety Administration, 2013b; Park & Im, 2020), the specific placement and form of DIT visuals need to be empirically determined so they require minimal cognitive demand and gazes away from the road. In conclusion, although the current DIT prototype is designed to minimize cognitive load and distraction, an important next step would be to investigate the effects of a DITs specific design elements on drivers' attention and ability to respond to emergencies as it is active.

Our current DIT prototype was designed to introduce and activate functionalities step by step. For example first Adaptive Cruise Control followed by a Lane Keeping System. While the acceptance of the DIT prototype appeared high in our simulator study (Chapter 8), we suggest to further investigate driver's willingness to use it in their own car. Some drivers may not be willing to go through the tutoring steps and just want to use all functions the moment they get in their new car. While it is not safe to let drivers use automated functions without any information, these drivers may be hesitant to buy a partially automated car if they cannot use all functions directly. On the other hand however, a DIT can make automated driving more approachable for drivers that are hesitant to use technology because it seems too complex. This can actually lead to increased adoption of partially automated cars. The willingness to use a DIT, and its consequent effect on automation use should therefore be further explored.

Additionally, although the DIT prototype was already evaluated in a mid-fidelity driving simulator to be able to thoroughly examine driver's take-over behaviour, an important next step would be to develop a prototype in an experimental vehicle, and study its use in a controlled on-road study. While driving behaviour patterns are similar in mid- and high-fidelity simulators and on-road studies, on-road studies are needed next to examine driver behaviour in a more natural setting with higher external validity. In relation to this, opportunities for the practical implementation of DITs in commercially available cars need to be explored. While full implementation by the manufacturer would allow for the latest model-specific information after-market solutions for existing cars may also be considered. The visuals on the windscreen can be achieved through an after-market HUD or by combining a tablet and a reflective transparent windscreen sticker (Project DIY, 2017). It would need to be further investigated how the functionality of the DIT could then be integrated with the car's automated functions especially as car manufacturers

currently do not make all information about their automated function publicly available.

Finally, while we studied the concept of a DIT within the scope of cars with lower levels of automation, it is also applicable for cars with more advanced automation that still require human interaction. Even with higher levels of automation, drivers need to be aware of the automation and know how and when they can use it. It would therefore be useful to extend our research and the applications of DITs towards cars with higher levels of automated systems.

9.3 Conclusion

This thesis reveals that drivers are currently insufficiently supported in understanding and appropriately using partially automated cars. They do not receive (ample) information from their car dealers, nor are they able to practise there. Additionally, there is no central source for model- and update specific information about their car's automation. Consequently drivers have to rely on trial-and-error and the owner's manual to learn about the automation, both of which we found to be inadequate in supporting appropriate automation use. Immediate and thorough measures need to be taken as this negatively impacts both traffic safety and the adoption of car automation.

An in-car solution is required to ensure that all drivers receive model specific information about the automation's functions and limitations before using it. We developed an adaptive Digital In-car Tutor prototype that explains the automated functions step-by-step on simple roads during regular driving trips. A key unique aspect of this Digital In-car Tutor is its adaptivity to the (complexity of the) driving situation in order to stimulate situated learning and avoid overloading the driver. Our research shows that while additional research is necessary a Digital In-car Tutor shows potential to positively affect appropriate automation use. This research delivers a solid basis for the improvement of in-car driver support aimed at helping drivers understanding and appropriately using their car's automation.

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Appendices

Appendices

Appendix A.1 – Consumer survey

1. Did you buy or lease a new car in the last two years?

Yes, I bought a new car.

Yes, I started leasing a new car.

Yes, I bought a second hand car.

No .

2. What brand is the car you bought/leased?

3. What car model did you buy/lease? (Example: Audi A4 Avant 2.0 2017) If you are not sure which exact model you have, please fill in as much as you do know about the model.

4. In what year was your car built?

5. How was the car delivered to you?

Delivery at home or at work without any personal help of a sales person.

Delivery at home or at work with personal help of a sales person.

I got it myself at the car dealer or lease company.

I got it myself at the car manufacturer. (For example through the 'Factory Delivery Experience' by Volvo in Torslanda Sweden, and the 'Pick up experience' by

Volkswagen

in Wolfsburg Germany).

Other, ...

6. Which of the following automated car systems does your car have? (Multiple answers possible.)

Cruise Control (CC). This system maintains a set speed.

Adaptive Cruise Control (ACC). This system maintains a set speed and a set distance to the car in front simultaneously.

Lane Keeping. This system keeps the car within the lane. The car steers itself to keep between the lane markings.

Automated Lane Change. The car changes lane by steering itself if the driver turns on the indicator.

Automated Parking. The car parks itself. In most systems, only the steering is automated and the driver still has to press the gas and brake pedals.

None of these systems.

I do not know.

Other, ...

7. How often do you use the following systems?

	Never	Sometimes	Regularly	Every time I drive	I do not know	Not applicable
Cruise Control (CC). This system maintains a set speed.						
Adaptive Cruise Control (ACC). This system maintains a set speed and a set distance to the car in front simultaneously.						
Lane Keeping. This system keeps the car within the lane. The car steers itself to keep between the lane markings.						
Automated Lane Change. The car changes lane by steering itself if the driver turns on the indicator.						
Automated Parking. The car parks itself. In most systems, only the steering is automated and the driver still has to press the gas and brake pedals.						

8. About which of these systems did you get information from the car dealer? (Multiple answers possible.)

Cruise Control (CC). This system maintains a set speed.

Adaptive Cruise Control (ACC). This system maintains a set speed and a set distance to the car in front simultaneously.

Lane Keeping. This system keeps the car within the lane. The car steers itself to keep between the lane markings.

Automated Lane Change. The car changes lane by steering itself if the driver turns on the indicator.

Automated Parking. The car parks itself. In most systems, only the steering is automated and the driver still has to press the gas and brake pedals.

I did not get information about any of these systems.

I turned down any information myself.

I do not know.

Other, ...

8a. Why did you turn down the information?

9. When did you receive information about any of the prior mentioned systems from the car dealer?

During the purchase contact.

During the delivery of the car.
 Both during the purchase contact and the delivery of the car.
 I did not get information about any of these systems.
 I turned down any information myself.

10. How did you get information about any of the prior mentioned systems from the car dealer?
 (Multiple answers possible.)

Verbal explanation by the car seller.
 Through (referral to) a brochure or information file.
 Through videos of the systems (shown by the seller).
 Through the owner's manual.
 Through (referral to) a website.
 By trying out the systems on the road together with the seller.
 Through an official training of one or multiple sessions.

Other,...

11a. If you had an official training, what parts did this training consist of?

Theoretical training.
 Practical training.
 A combination of theory and practical training.
 I don't know.

11b. Can you further describe the process of the training?

12. To what extent did the information cover the following topics?

	Not at all	Little	Not extensive/ not little	Extensive	Very extensive
The functionalities of the system. [What the system can do]					
Operating/handling the system.					
The capabilities and limitations of the system. [In what situations does the system work or not]					
The hardware and technical functioning of the equipment like sensors and cameras.					

13. After getting the information:

	Totally disagree	Disagree	Neutral	Agree	Totally agree
I know which automated systems are in my car.					
I understand the functionalities of the automated systems.					
I understand how to operate/handle the systems.					
I understand the capabilities and limitations of the system. [In what situations does the system work or not]					
I understand the equipment that the systems consist of and how these work.					

14. How satisfied were you with the way that you were provided with information about the automated systems?

Very dissatisfied.

Dissatisfied.

Neutral.

Satisfied.

Very satisfied .

15. What where you satisfied about?

16. What where you dissatisfied about?

17. Where do you look for information about the automated systems in your car in case you have any questions? (Multiple answers possible.)

In the paper owner's manual.

In the digital owner's manual.

At friends, family or colleagues.

At a car dealer or lease company.

On the internet.

I never look up information about this.

18. What websites do you mainly use for looking up information about the automated systems in your car in case you have any questions? (Multiple answers possible.)

Search engine like Google.com.

The car manufacturer's website.

The ANWB website.

A car news website such as Autoweek.nl, Topgear.nl of autowereld.nl.

A video sharing website like youtube.com or vimeo.com.

I don't know.
Other, ...

19. What is your gender?

Male.
Female.

20. What is your age?

21. What is your highest education level?

None or primary education.
Secondary education.
Associate's degree.
Bachelor's degree.
Master's degree or higher.

22. I mainly travel:

More by public transport than by car.
More by car/motorcycle than by public transport.
Just as much by car/motorcycle as by public transport.
I (almost) never travel by car/motorcycle or public transport.

23. I am interested in new technology (for example gadgets and apps).

Totally disagree.
Disagree.
Neutral.
Agree.
Totally Agree.

24. I am interested in the latest developments in car technology.

Totally disagree.
Disagree.
Neutral.
Agree.
Totally Agree.

Appendix A.2 – Car seller survey

1. Does your company sell passenger cars?

Yes.

No/almost never.

2. Which car brands do you sell? (Multiple answers possible.)

3. Do you sell cars that are built after 2012?

Yes, (almost) always.

Yes, regularly.

Yes, sometimes.

No, I primarily sell cars that were built before 2012.

4. Which of the following systems are present in the cars that you sell? (Multiple answers possible.)

Adaptive Cruise Control (ACC). Adjusts its speed to the traffic.

Lane Keeping. The car follows the lane by detecting the road lines.

Automated Lane Change. The car automatically changes lane if the driver turns on the indicator.

Automated Parking. The car parks by itself. In most cases, only the steering is automated, the driver still needs to brake and accelerate.

Emergency brake. The car brakes automatically in case to avoid an imminent crash.

Live navigation system (TMC live).

Parking sensors and/or cameras.

Lane departure warning. Warns the driver when the car is (almost) crossing the road lines. For example by sound, light, symbols and/or a vibrating steering wheel.

Blind spot detection. Warns the driver if an object is in the blind spot.

Distance alert.

Intelligent Speed Adapt. A system that helps the driver to keep to the speed limit.

Traffic sign recognition.

Driver fatigue recognition.

None of these systems.

I do not know.

5. In general, do you think that you get enough information (from car manufacturers, importers, your car dealership, holding, a nearby dealer or wholesaler) to provide customers with information about ADAS?

Yes, I get sufficient information.

No, I get insufficient information.

No, I get no information.

6. Who provides you with information about ADAS? (Multiple answers possible.)

- Car manufacturers/importers.
- My location or holding.
- A nearby car dealer.
- An education company (i.e. Innovam).
- My garage brand.
- My wholesaler.
- I receive (almost) no information.
- I look up the information myself.
- I do not know.
- Other, ...

7. What is your most important reason to look up ADAS information yourself?

- I do not receive (enough) information from car manufacturers, importers, my location or holding, nearby dealers, my garage brand, my wholesaler or an education company.
- I do not receive the correct information from car manufacturers, importers, my location or holding, nearby dealers, my garage brand, my wholesaler or an education company.
- The information i receive is confusing or difficult to understand.
- I think it is interesting.

8. Where do you (on your own initiative) look for information about ADAS? (Multiple answers possible.)

- I contact a stakeholder organization such as BOVAG.
- In the paper owner's manual.
- In the digital owner's manual.
- By asking colleagues.
- On video websites such as youtube.com.
- On an internet forum.
- On different websites.
- On an app.
- Other,...

9. How do you receive information about ADAS?

- A colleague explains it to me.
- I am referred to the owner's manual.
- I am referred to a website.
- Through an app.
- Through an information brochure.
- By trying out the functions on the road.
- Through a training that deals with ADAS by the car manufacturers, importers or my garage brand. (For example an information meeting or practical training.)
- Through a training from that deals with ADAS my location or holding. (For example an information meeting or practical training.)
- I receive (almost) no information.
- I look up the information on my own.

Other,...

9a. To what app or website are you referred?

10. Complete the following sentence with (1) very good, (2) good, 3 (sufficient), 4 (poor), 5(very poor).

The availability of the provided trainings is ...

The capacity of the provided trainings is ...

The content of the provided trainings suits my daily sales tasks ...

11. Describe what the provided trainings you receive consist of.

12. How often do you receive a general ADAS training?

Once.

Once every three months.

Once every year.

Less than once per year.

13. Do the model specific trainings that you receive discuss ADAS?

Always.

Sometimes.

No.

N/A.

14. From whom do you wish to receive ADAS information?

The car manufacturer/importer.

My location or holding.

A nearby dealer.

My garage brand.

My wholesaler.

The government.

The BOVAG (A Dutch stakeholder organization).

The RAI (A Dutch stakeholder organization).

The ANWB ((A Dutch stakeholder organization).

I do not want any ADAS information.

Other,...

15. What information do you expect to support you in providing information about ADAS to customers?

Digital education materials that are aimed at car sellers.

Paper education materials that are aimed at car sellers.

Digital education materials aimed at the customer that can be used directly during the customer contact.

Paper education materials aimed at the customer that can be used directly during the customer contact.

A training for car sellers.

16. Rate the following statements from 1 (Strongly Disagree) to 5 (Strongly Agree).

In order to give complete and correct information about ADAS to customers I:

I do not have enough time during the customer contact moments.

I lack the right education.

I lack the right materials.

I do not get enough time or resources to investigate ADAS myself.

17. When u are talking to customers about a car they are interested in, how often do you give them information about ADAS?

Never.

Rarely.

Sometimes.

Often.

(Almost) Always.

17b. You indicate that you only sometimes or rarely provide ADAS information to customers. Which statement applies most to your situation?

I usually start informing the consumers about ADAS on my own initiative.

I usually only give ADAS information when the customer asks me about it.

18. When do you give information to customers about ADAS?

When the customer is first looking for a new car. (The orientation phase)

During the definitive sale meeting with the customer.

When the car is delivered to the customer.

After the car is delivered to the customer (for example during a maintenance appointment).

19a. How do you inform customers about ADAS information? (Multiple answers possible.)

By a verbal explanation.

By referring them to a website.

By referring them to the owner's manual.

Through an information brochure.

Through an app.

During a test drive where I (the car seller) drive and show the different systems.

During a test drive where the customer is drives and tests out the different system.

Through an instruction system in the car itself (a tutorial).

We (our location or holding) provide our own training to customers.
We provide trainings through an importer.
We provide trainings through another party (other than importers, for example a driving school).

19b. To which websites or apps do you refer customers to look up information about ADAS?

19c. Describe the ADAS training that you or another party provides for the customer.

20. What is your gender?

Male.

Female.

21. What is your age?

22. What is your job description?

Appendix B.1 - Knowledge test on system description

Some questions are presented regarding the information you just had the opportunity to read. After this test you will continue to the driving simulator.

1.The traffic sign recognition:

- Detects standard maximum speed signs and adjusts the cars speed accordingly
- Detects standard maximum speed signs but you have to adjust the speed of the car yourself
- Only detects priority signs

2.The adaptive cruise control:

- Automatically overtakes vehicles on the highway
- Keeps 1.5 m distance to the following vehicle
- Accelerates to the maximum speed if there is no leading vehicle or obstacle

3.The obstacle detection:

- Detects no cars
- Detects cars
- Is not present in the described car system

4.The route navigation:

- Follows the given route in the navigation through a combination of GPS, the Odometer and road lines
- Follows the lane based only on road lines
- Is not present in the described car system

5.The ultrasonic sensor detects objects all around the vehicle on:

- Long distance (250 m)
- Medium distance (150 m)
- Very short distance (8 m)

6.The radar detects objects in rain and fog:

- True
- False

7.The system contains multiple cameras to detect objects from short to long distance

- True
- False

8.The system contains a Lidar

- True
- False

Appendix B.2 – System description

On this information sheet, you will find some information about a partially automated car. Please take your time to read this information carefully as this is of great importance for the study. After about 5 min you will be called by the researcher for the next part of the study. You can always ask for more time to read this sheet if necessary. This information sheet will first explain which systems and technical equipment is in the car and what functions they have. After this, a short explanation on how the systems work together is provided.

Overview

Figure B.1 below shows which automated systems are in the car (left), and through what technical equipment they function (right).

Figure B.1. Automated systems in the provided car system.

Systems, equipment and functions

Automated systems

The partially automated car has the following automated systems and function:

(1) Obstacle detection

- Detects road users, objects, traffic lights, traffic signs, parking spaces, road edges, road lines, intersections.

(2) Adaptive cruise control (ACC)

- Keeps two car lengths distance to the leading vehicle
- Accelerated to the maximum speed when there is no leading vehicle or obstacle

(3) Traffic sign detection

- Detects standard maximum speed signs and adjusts its speed accordingly
- Detects priority signs
- Follows the set legal rules and guidelines of priority signs

(4) Route navigation

- Determines car location based on GPS and Odometer
- Follows the entered route
- Follows the road on the right side according to both road lines and physical road edges
- Follows the set legal rules and guidelines of road lines
- Stops and manoeuvres for obstacles

Physical equipment

(1) Camera's

- 3 FRONT cameras. Detects obstacles in front of the vehicle on different distances and field of views (see technical specifications)
- 4 SIDE cameras. Detects obstacles on the side of the vehicle on different distances and field of views (see technical specifications)
- 1 BACK camera. Detects obstacles on the back of the vehicle

(2) Radar

- Detects obstacles in front of the car, regardless of weather conditions (see technical specifications)

(3) Ultrasonic sensor

- Detects obstacles around the entire vehicle on short distance. (see technical specifications)

(4) GPS sensor

- Detects the GPS location of the vehicle

(5) Odometer

- Measures the travelled distance

Working ranges of detection equipment

Table B.1.

Working ranges of the equipment.

Equipment			Reach	Function
Cameras	Front	Main front	Max distance 150 m 50° field of view	Detects obstacles in front of the vehicle on medium to short distance
		Narrow front	Max distance 250 m 35° field of view	Detects obstacles in front of the vehicle on long distance, in a narrow field of view
		Wide front	Max distance 60 m 150° field of view	Detects obstacles in front of the vehicle on short distance, in a broad field of view
	Side	Aimed at front	Max. distance 80 m 90° field of view	Detects obstacles on the side of the vehicle on short distance
		Aimed at back	Max. distance 100 m	Detects obstacles in the blind spot of the vehicle on short to medium distance
	Back		Max. distance 50 m	Detects obstacles behind the vehicle at a short distance
Radar	Front		Max. distance 160 m	Detects obstacles in front of the vehicle on medium distance, regardless of the weather conditions
Ultrasonic sensor	Around		Max. distance 8 m 360° field of view	Detects obstacles around the entire vehicle on very short distance
All equipment detects objects higher than 30 cm from the ground				

Figure B.2. Illustration of the working ranges of the radars, cameras and sonar system. Adapted from [www.Tesla.com](https://www.tesla.com/nl_NL/autopilot) website, by Tesla ©, 2018, retrieved from https://www.tesla.com/nl_NL/autopilot.

Requirements for optimal performance

- The equipment functions optimally on a *level asphalt road*.
  - The obstacle detection detects *standard* road lines that indicate the course of the road. Other road markings are not detected.
  - The road sign detection detects *standard* round maximum speed signs with a red border. Other maximum speed signs are not detected.

Appendix C.1 – Evaluation of current HMI of partially automated cars

Table C.1.
TOR feedback - Commercial cars.

TOR – commercial cars							
Car brand	System	Suppleness		Bodily experience		Situatdness	
		Temporal output mode	Time to take over	Social cues	Output of TOR	Input to disengage automation	Adaptive to driver situation
Audi (Audi MediaCenter, 2017; CHNL, 2017)	Audi AI traffic jam pilot	S	Up to 10s	Y (Hands on wheel icon)	V (Display), A (Beep), C/E (Brake, Belt tightening)	P (Wheel, Pedals, Button)	N
BMW (BMW (Bayerische Motoren Werke), 2015, 2018; eGear Tv, 2017)	Steering & Lane Control Assist including Traffic Jam Assist	-	-	-	-	-	-
Cadillac (Cadillac, 2018; SlashGear, 2017)	Super Cruise	Once, before deactivation	N/A	Y (Hands on wheel icon)	V (Display, Lighting), A(Beep), H (Vibration in seat)	P(Wheel, Pedals, Button)	N
Mercedes (Mercedes-BenzKing, 2018; Mercedes- Benz, 2016, 2017)	Drive Pilot	-	-	-	-	-	-
Tesla (Nick's Tesla Life, 2016; Tesla, 2015, 2018; Tesla Family, 2017)	Traffic aware cruise control and Autosteer	-	-	-	-	-	-
Volvo (Volvo, 2018; Volvo Cars, 2017b)	Pilot Assist	-	-	-	-	-	-

Table C.2.
TOR feedback - Literature concepts.

TOR – literature concepts						
Source	Suppleness		Bodily experience		Situatdness	
	Temporal output mode	Time to take over	Social cues	Output of TOR	Input to disengage automation	Adaptive to driver
(Kerschbaum et al., 2015)	O, before hazard	D	N	V (Display), A (Beep), V/H (Shape change)	P (Wheel, Pedals, Button)	N
(Borojeni et al., 2017)	O, before hazard	D	N	A (Beep), C (Vibration)	P (Wheel, Pedals, Button)	N
	O, before hazard	D	N	A (Beep), V/C (Shape change)	P (Wheel, Pedals, Button)	N
(Naujoks et al., 2017)	S,I	“Sufficient time to take over”	Y (Hands on wheel)	V (Display)	P (Wheel, Pedals)	N
(Politis et al., 2017)	O, before hazard	D	Y (Use of female distressed voice)	V (Display), A (Verbal, Beep), C(Vibration)	P (Wheel, Pedals)	N
(Zimmerman & Bengler, 2013)	S	“Sufficient time to take over”	N	V (Display)	P (Button, Pedals)	N
(Hester et al., 2017)	O, before hazard	D	N	A (Beep)	P (Wheel, Pedals)	N
(Blanco et al., 2016)	O, before hazard	D	N	A (Verbal)	P (Wheel, Pedals)	N
	S,I	50s	N	V (Display, Lighting)	P (Wheel, Pedals)	N
	S,I	50s	N	V (Display, Lighting), C(Vibrations)	P (Wheel, Pedals)	N
(van der Heiden et al., 2017)	S,I	20s	N	A (Beeps)	P (Wheel, Pedals)	N
	O, during deactivation	D	N	A (Beeps, verbal)	P (Wheel, Pedals)	N

(Toffetti et al., 2009)	S	"A few minutes"	N	V (Display), A (Beeps)	P (Wheel, Pedals)	N	N
	S	"A few minutes"	N	V (Display), A (Verbal)	P (Wheel, Pedals)	N	N
(Petermeijer, Bazilinsky, Bengler, & De Winter, 2017)	O, before hazard	D	N	A (Beeps)	P (Wheel, Pedals, Button)	N	Y (Feedback is directional)
	O, before hazard	D	N	H (Vibration)	P (Wheel, Pedals, Button)	N	Y (Feedback is directional)
	O, before hazard	D	N	A (Beeps), C (Vibration)	P (Wheel, Pedals, Button)	N	Y (Feedback is directional)
(Walch, Lange, Baumann, & Weber, 2015)	O, before hazard	D	N	V (Display), A (Beeps, verbal)	P (Wheel, Pedals)	N	Y (TOR changes to the weather condition)
	O, before hazard	D	N	V (Display), A (Beeps, verbal)	P (Wheel, Pedals)	N	N
	O, before hazard	D	N	V (Display), A (Beeps, verbal)	P (Wheel, Pedals)	N	N
(Duthoit, Stieffermann, Enrègle, Michon, & Blumenthal, 2018)	O, before hazard/deactivation	60s	N	C (Vibration)	N/A	N	N
(Petermeijer, Cieler, & De Winter, 2017)	O, before hazard	D	N	C (Vibration)	P (Lever)	N	Y (Direction pattern corresponds to the suggested/required action of the driver)
(Lorenz et al., 2014)	O, before hazard	D	N	V (Display), A (Beeps)	P (Wheel, Pedals)	N	Y (Colour of lane overlay AR adapts to the safety to continue on that lane)
(Langlois & Soualmi, 2016)	S,I	10s	Y (Hands on wheel)	V (Display)	P (Button)	N	Y (Lines show restrictions of trajectory after to)

(Kim, Jeong, Yang, Oh, & Kim, 2017)	O, before hazard	D	N	V (Display), A (Beeps)	P (Wheel, Pedals)	N	N
(Borojeni et al., 2016)	O, before hazard	D	N	V (Lighting), A (Beeps)	P (Wheel, Pedals)	N	Y (Location/movement direction of the lighting indicated suggested steering direction)
(van den Beukel et al., 2016)	O, before hazard	D	N	A (Beeps)	P (Wheel, Pedals)	N	Y (Sound/type of TOR depends on the required actions)
	O, before hazard	D	Y (Hands on wheel)	V (Display), A (Beeps)	P (Wheel, Pedals)	N	Y (Colour/type of TOR depends on the required actions)
	O, before hazard	D	N	V (Lighting), A (Beeps), C (Vibration)	P (Wheel, Pedals)	N	Y (Colour/type of TOR depends on the required actions)
(Melcher et al., 2015)	O, before deactivation	10s	Y (Hands on wheel)	V (Display), A (Beeps), E (Brake Jerk)	P (Wheel, Pedals)	Y (Request also appears on phone when the driver is using it)	N
(Naujoks et al., 2014)	O, during deactivation	D	Y (Hands on wheel)	V (Display), A (Beeps)	P (Wheel, Pedals, Button)	N	N

Table C.3.
HMI during automation - Commercial cars.

Car brand	System	Feedback HMI during automation – commercial cars				
		Suppleness	Bodily experience		Situatedness	Form is adaptive to driving situation
		Temporal output of HOWW	Time to place hands on wheel after HOWW before system disengages	Social cues	Output of HMI system	Form is adaptive to driver
Audi (Audi MediaCenter, 2017; CHNL, 2017)	Audi AI traffic jam pilot	-	-	Y (Use of 'hands on wheel' symbol)	V (Display), C (Vibration), A (Beeps)	Y (Full TOR is started if driver is performing unallowed activities or keeps their eyes closed for long periods)
BMW (BMW Bayerische Motoren Werke), 2015, 2018; eGearTv, 2017)	Steering & Lane Control Assist including Traffic Jam Assist	S,I	N/A	Y (Use of 'hands on wheel' symbol)	V (Display), C (Vibration), A (Beeps)	Y (Detected lane markings, detected vehicles, detected speed limit)
Cadillac (Cadillac, 2018; SlashGear, 2017)	Super Cruise	S,I	N/A	Y (Use of 'hands on wheel' symbol)	V (Display, Lighting), C (Vibration), A (Beep, Verbal)	Y (Detected lane markings, detected vehicles, detected speed limit)

Mercedes (MereBenzKing, 2018; Mercedes- Benz, 2016, 2017)	Drive Pilot	S,I	N/A	Y (Use of 'hands on wheel' symbol)	V (Display), C (Vibration), A (Beeps)	Y (HOWW, if hands are off)	Y (Detected lane markings, detected vehicles, detected speed limit)
Tesla (Nick's Tesla Life, 2016; Tesla, 2015, 2018; Tesla Family, 2017)	Traffic aware cruise control and Autosteer	S,I	N/A	Y (Use of 'hands on wheel' symbol)	V (Display), C (Vibration), A (Beeps)	Y (HOWW, if hands are off)	Y (Detected lane markings, detected vehicles, detected speed limit)
Volvo (Volvo, 2018; Volvo Cars, 2017b)	Pilot Assist	S,I	N/A	Y (Use of 'hands on wheel' symbol)	V (Display), C (Vibration) , A (Beeps)	Y (HOWW, if hands are off)	Y (Detected vehicles, detected speed limit)

Table C.4.
HMI during automation - Literature concepts.

Source	Suppleness Social cues	Bodily experience Output of HMI system	Situatdness	
			Form is adaptive to driver	Form is adaptive to driving situation
(Beller et al., 2013)	Y (Use of social gesture "uncertainty gesture", face and hands)	V (Display)	N	Y (An uncertainty symbol -face and hands- appears according to the situation)
(Gowda et al., 2014)	N	V (Display)	Y (Shows detected driver condition)	Y (Detected environment. Next action of the car within the situation)
(Hester et al., 2017)	Y (Asks non-task related questions, small talk)	A (Verbal)	N	Y (Questions and remarks on the current driving situation)

(Helldin et al., 2013)	N	V (Display)	N	Y (Level of certainty adapts to the situation and car capabilities)
(Hock et al., 2016)	N	A (Verbal), V (Display, VR)	N	Y (Level of information is adapted to the situation)
(Naujoks et al., 2017)	N	A (Verbal), V (Display)	N	Y (Detected environment. Next action of the car within the situation)
(Karatas et al., 2017)	Y (Use head movement to redirect gaze, shared gaze)	C (Movement), V (Lighting)	Y (Trying to engage in mutual gaze is started when the driver is not paying attention enough to the road)	N
(Koo et al., 2015)	N	A (Verbal)	N	Y (Next action of the car within the situation)
(Langlois & Soualmi, 2016)	N	V (Display)	N	Y (Detected environment. Next action of the car within the situation)
(Lorenz et al., 2014)	N	V (Display)	N	Y (Colour of lane overlay AR adapts to the safety to continue on that lane)
(Nees et al., 2014)	N	A (Verbal, Auditory icon sound)	N	Y (Car state. Detected hazard)
(Rezvani et al., 2016)	Y (Frown or smile to suggest system confidence)	V (Display)	N	Y (Detected environment. Level of certainty adapts to the situation and car capabilities)
(Telpaz et al., 2015)	N	C (Vibrations)	Y (Message is only provided if driver is looking away from task)	Y (Location of vibration in seat changes according to detected vehicles)
(Wi et al., 2017)	N	C (Vibrations)	Y (Designed for visually impaired drivers)	NA
(van den Beukel et al., 2016)	N	A (Beeps)	N	N
	Y (Use of 'hands on wheel' symbol)	V (Display), A (Beeps)	N	N
	N	V (Lighting), A (Beeps)	N	Y (Location and colour of illumination changes to place and type/degree of hazard)

Appendix D.1 – Classification of observed events in driving instructors

Table D.1.

Overview of the observed non-verbal events by the driving instructors.

Behaviour category	Behaviour event	Code
A)Feedback	Tumbs up	BA1
	Tumbs down	BA2
	Head nod	BA3
	Head shake	BA4
B)Direct attention	Point outside car	BB1
	Point inside car	BB2
	Hand straight up, palm open facing forward (Pay attention/focus)	BB3
C)Indicate desired behaviour	Wave movement forward	BC1
	Up down movement flat hands	BC2
	Hand gesture “come”	BC3
	Hand movement toward desired direction	BC4
	Draw situation	BC5
D)Reflect on previous situation	Act out situation with props/hands	BC6
	Perform the action himself	BC7
	Draw situation	BD1
	Act out situation with props/hands	BD2
	Draw situation	BE1
E)Reflect on current situation	Act out situation with props/hands	BE2
	Draw situation	BF1
F)Explain traffic rules	Act out situation with props/hands	BF2
	Draw situation	BG1
G)Explain car equipment	Act out situation with props/hands	BG2
	Adjust car system settings	BG3
H)Test theory knowledge	Draw situation	BH1
	Act out situation with props/hands	BH2

Table D.1.

Overview of the observed verbal events by the driving instructors.

Speech category	Speech event	Code
A)Feedback	Positive feedback	SA1
	Negative feedback	SA2
B)Direct attention	Name point of interest or tell student to look	SB1
C)Indicate desired behaviour	Name required action such as “brake” or “shift”	SC1
D)Reflect on previous situation	Discussion or question about the previous situation	SD1
	Discussion any previous situation that occurred during another lesson	SD2
E)Reflect on current situation	Discussion or question about the current situation	SE1
F)Explain traffic rules	Recite or discuss general traffic rules	SF1
G)Explain car equipment	Explain car equipment such as navigation or Cruise Control.	SG1
H)Test theory knowledge	Question about general traffic rules	SH1
I) Other	Non-driving related	SI1

Appendix D.2 - Acceptance questionnaire

The following questions are specifically about the training system you experienced!

Please indicate for each statement to what extent you (dis)agree. (1- Strongly agree, 7- Strongly disagree)

Perceived ease of use.

1. I find the training system easy to use
2. Learning how to use the training system is easy for me
3. It is easy to become skilful at using the training system

Perceived usefulness.

4. The training system makes learning about the automated car systems easier
5. The training system makes using the automated car systems easier
6. The training system makes using the automated car systems safer

Attitude.

7. Using the training system in an automated car is a good idea
8. I am positive towards using the training system in an automated car
9. Using the training system is annoying
10. Using the training system is frustrating

Intention to use.

Imagine that you own the partially automated car that you experienced today.

11. I would actively use the training system in my partially automated car

Self-efficacy.

12. I feel confident in using the training system
13. I have the necessary skills to use the training system

Social norm.

Imagine that you own the partially automated car that you experienced today.

14. People who are important to me think I should use the training system

Appendix D.3 - Digital In-car Tutor prototype visual- and verbal communication

Table D.3.

An overview of all visual- and verbal communication of the DIT prototype used in the driving simulator study described in Chapter 8.

Driving scenarios in Session 1			
ID	Scenario	Visual	Audio
ACC1	Straight highway	No image was displayed during this audio	Hi! I will be your tutor for today and help you explore all the automated systems in this partially automated car. There are a few different systems that together make this car drive by itself under specific conditions. It is very important to understand these, so you know when you can use the automation safely. Don't worry, we will go through the systems step-by-step and try them out together! For now, you can just start to drive manually. I will get back to you when it is safe to try out the first function. Let's start by explaining the first system Adaptive Cruise Control. It keeps the car at a set speed, and automatically speeds up, and slows down our car, to keep a set distance to the car ahead. Our car has several camera's which are used to detect the car ahead of you. Note. The depicted car is a visual overlay, shown to explain the system.

Note. The depicted car is a visual overlay, shown to explain the system.

There are some conditions when the Adaptive Cruise Control cannot function safely and you should not turn on the automation. These include certain types of weather conditions such as heavy fog, or rain as they obstruct the cameras. Also, the car cannot brake in time for stationary objects and road users when driving faster than 80 km/h.

When you turn on the system you will notice that the steering wheel is moving. I will explain later why this is, but for now you do not need to steer the car yourself. But enough talking, let's try it out ! Always make sure that you are in the middle of the lane and your steering wheel is straight when you turn on the automation. Press the blue button on the wheel to turn on the automation. To turn it off simply press the blue button once more.

Fog

It looks like some fog is coming up. Remember, the Adaptive Cruise Control cannot function properly in rain as it can obstruct the camera's view.

If driver disengages automation: That went very well! It looks like the weather is clearing up so you can turn the automation back on. Remember, if the car's cameras are obstructed you should drive yourself.

If driver does not disengage automation: That did not go so well. Remember if the car's cameras are obstructed you should drive yourself.

ACC2

LC1 Curved Rural

Let's continue to the next function: Lane Keeping. Lane Keeping Keeps the car between the road lines by gently steering. The automation can steer by itself on straight roads but also in curves. It can also cross small intersections.

Lane Keeping also has trouble dealing with overly complex road lines and cannot keep within its lane if road markings are missing. Remember that if you press the blue button, the entire automated system is activated. Try it out on this road.

A curve is coming up. The road lines are clearly visible and the curve doesn't seem very sharp.

If driver does not disengage automation: Great! The road lines were very clear and the curve was not very sharp, so the automation was very able to drive itself.

If driver disengages automation: If you don't feel safe you can always take back control. But remember that the car is able to drive through non sharp curves with clear road lines.

A small intersection without traffic is coming up. The car can usually safely cross small intersections.

If driver does not disengage automation: Great! The car can usually cross small intersections.

If driver disengages automation: If you don't feel safe you can always take back control. But remember that the car can usually safely cross small intersections.

No image was displayed during this audio

LC2 Roadworks

This highway is a good place to further try out the automation. You can now turn on the automation.

There seems to be roadwork coming up. Remember that the automation cannot deal with overly complicated road lines.

If driver disengages automation: Good decision to take back control. Those complicated road lines would have made it very difficult for the car to decide where to drive.

If driver does not disengage automation: That did not go so well. The complicated road lines made it very difficult for the car to decide where to drive. Turn off the automation if the road lines are too complicated, not very visible or absent.

This seems like a great time to explain and try the Obstacle Detection of the automation.
Obstacle detection detects obstacles and road users through the car's cameras.

The car will automatically brake if any of these are in the way of the car.

Obstacle Detection does not work effectively if the cameras' view is obstructed.

Remember that the car cannot brake in time for stationary objects and road users when driving faster than 80 km/h. You can try out the function now.

A pedestrian is crossing the road. We are driving very slow and the pedestrian is clearly visible.

If driver does not disengage automation: Fantastic. The pedestrian was well visible and we were driving very slow so the car was able to detect the pedestrian and brake. If driver disengages automation: If you don't feel safe you can always take back control. But remember that the car is able to detect and stop for clearly visible road users and obstacles if we are driving slowly.

OD2
Pedestrian obstructed view

The camera's view is largely blocked. The car cannot see any pedestrians that might cross. (Please note that this comment was made closer to the obstruction than shown in this image) If driver disengages automation: Taking back control was the right thing to do to be safe. The camera's view was obstructed.

If driver does not disengage automation: That did not go so well. The camera's view was obstructed. Remember that anything blocking the camera's view will limit the car from detecting and braking for road users and objects

TS1
Priority signs

The automation is also able to detect traffic lights and standard priority signs through the cameras. The car will give and take priority to other road users including pedestrians and cyclists accordingly.

Be aware that the system does not recognize intersections without any signs or traffic lights so it will not give priority in these situations. Try out the function now

A red traffic light is detected. It looks like we will have to wait for it to turn green.

If driver does not disengage automation: Fantastic. The intersection had clear traffic lights and was therefore able to give priority.

If driver disengages the automation: It may not have been necessary to turn off the automation as a clear traffic sign was detected. Remember that the car will detect and give priority according to traffic signs and traffic lights.

TS2 Unsignalised intersection

A dangerous unsignalized intersection is detected. If driver disengages automation: Very well done on taking back control. The car did not detect any traffic lights or signs so he would not have given priority and would have need to make an emergency break for the car on the right.

If driver does not disengage automation: That did not go so well. The car did not detect any traffic lights or signs so he did not give priority to the car and needed to make an emergency break. Only when a traffic light or priority signs indicate the priority order AND the car's cameras are unobstructed can he give and take priority.

RM1 Pedestrian crossing

The last part of the automation that I will explain is the Priority road markings detection. This detects standard priority road markings through the cameras such as pedestrian crossings. As with the traffic lights and priority signs, the car will then give or take priority accordingly.

As with the other functions, it cannot function safely if the cameras are obstructed or when the road markings are not clearly visible. Try out the automation now

A pedestrians crossing is coming up. It is clearly visible and a pedestrian is detected near. (Please note that this comment was made closer to the pedestrian crossing)

If driver does not disengage automation: Great. The pedestrian crossing was clearly visible, and we were driving slower than 80 km/h so taking over was likely not necessary.

If driver disengages the automation: The pedestrian crossing was clearly visible, and we were driving slower than 80 km/h so taking over may not have been necessary

RM2

A last very important remarks about the automation. The system cannot deal with other road users that do not obey the traffic rules indicated by the traffic lights and traffic signs

This includes emergency vehicles that break for example priority rules. Always take back control in these situations.

No road lines are detected. The automation is not able to keep within the lanes if there are no road lines.

If driver disengages the automation: Very well done on taking back control. The car did not detect any road lines so it would not have been able to take the curve safely

If driver does not disengage automation: That did not go so well. The car did not detect any road lines so it could not take the curve safely.

Summary

Summary

Part I - Introduction

Commercial cars are increasingly equipped with automated functions that simultaneously yet temporarily take over the longitudinal and/or lateral control with the goal to increase traffic safety and driver comfort. However, drivers not only need to supervise these systems, they also need to decide themselves when it is (un)safe to use them. If the automation is used outside its Operational Design Domain (ODD) (i.e. in situations for which the automation was not designed) traffic safety can be jeopardized. On the other hand, if the automation is not used within its ODD, any potential benefits are lost. It is therefore crucial that automated car systems are used appropriately (i.e. within their ODD). In order to use an automated car system appropriately, the driver needs to have an accurate understanding of its functions, capabilities, limitations and ODDs. However, creating this understanding can be extremely difficult considering the wide variety of complex automated systems that are entering the market. Multiple recent studies already show a lack of awareness and understanding of drivers about the automation in their car (Braitman et al., 2010; Harms & Dekker, 2017; McDonald, McGehee, et al., 2016; Onderzoeksraad voor Veiligheid, 2019). If left unaddressed, this will lead to inappropriate automation use and consequently negate any potential automation benefits or even endanger traffic safety. It is therefore crucial that drivers are supported in understanding and using the automation in their car. This support may be provided through the car's Human Machine Interface (HMI) to ensure that all drivers receive the same (and long-term) support. The goal of this thesis was therefore to: explore, develop and evaluate an in-car Human Machine Interface (HMI) to support drivers in understanding and appropriately using their car automation.

Part II - Current state of informing drivers about partially automated cars

Before designing any driver support to support driver's understanding of partially automated cars, we explored how drivers are currently supported (both before and while driving) in learning about and appropriately using the automation in their car. This was examined through several different studies in Part II of this thesis. First, two nation-wide surveys were distributed in The Netherlands among car buyers and -sellers to evaluate the way that they currently receive (or look up) information about car automation (**Chapter 3**). The results of this study show several issues about the way that both consumers and car sellers are informed about ADAS. First of all, there is a lack of complete, accurate and understandable pre-drive information for car buyers (i.e. information that drivers receive or look up before driving). What is worrisome is that especially the capabilities and limitations of the automation are hardly discussed. Second, there is a lack of a centralized, model specific, updated and reliable information source for both car buyers and car

sellers. Third, hardly any car buyers are able to try out their car's automation at the dealership or receive training. This lack of information leads to the fact that drivers mainly rely on trial-and-error and the owner's manual to learn about their car's automation.

Next, we conducted a driving simulator study to examine whether, and how, the most conventional ways that drivers learn about car automation (i.e. owner's manuals and trial-and-error) actually support appropriate automation use (**Chapter 4**). The participants were split into two groups: the first received no information about the system while the second did receive specific information about functionalities and system limitations. Each participant was seated in a driving simulator and was shown first person videos of a partially automated car driving in multiple city situations. They had to press a button on the steering wheel if they felt that the car could no longer cope with the situation. Each video was categorized as 'requires a take-over' or 'does not require a take-over' before the experiment, based on the same system descriptions the experimental group received. Overall, the system information did not appear to support the participants in correctly deciding whether to take over or to rely on the system. Owner's manuals do not appear to provide drivers with the necessary tools to be able to decide when it is (un)safe to use automated car systems.

Even if drivers do not receive (sufficient) information beforehand about the car's automation, all drivers are confronted inside the car with its HMI which may have a large influence on drivers' understanding and use of the automation. The next step was therefore to investigate how current car HMI inform drivers about the automation in the car, and to identify unused design opportunities (**Chapter 5**). Until now, the research and development of driver support through in-car HMI has been mainly addressed from a traditional cognitive psychology or human centred design perspective. Our review however took the perspective of a relatively new paradigm within interaction design: embodied interaction. Embodied interaction proposes that all knowledge and sense-making of the world emerges from a continuous and simultaneous interaction with the world (van Dijk et al., 2014). By discarding the idea that cognition only occurs in the mind, new design spaces may be discovered. We reviewed the HMI review of both commercially available cars and of research concepts on three core characteristics of embodied interaction: suppleness, bodily experience and situatedness. The results of this study identified several design spaces that are currently underutilized. For the HMI during automation, new designs are encouraged to explore a wider variety of output methods and focus on adaptivity to the driver. For take-over requests, new designs are encouraged to include (more) social cues, in- and output methods and focus more on adaptivity to the driver. Including these aspects may contribute to driver's understanding of the automation within a specific context and consequently more fluent and natural transitions between manual and automated driving

In summary, we conclude that drivers currently do not receive sufficient information and training before, and while, driving to be able to understand and appropriately use the automation in their cars. This leads drivers to rely on trial-and-error and the owner's manual, both of which we showed to be unsafe and incomplete methods to learn about car automation. The studies lead us to determine that it is necessary to specifically develop an in-car HMI to aid drivers in understanding and appropriately using their partially automated cars. By including the support in the car itself, all drivers receive information about their car's automation. This support is provided even if they didn't receive any external information or training, nor actively looked for information themselves. Additionally, drivers can be informed and supported for a longer period of time, in contrast to one time training at a driving school or in a simulator. Next, an in-car HMI allows for exploring driver- and environment adaptive information as suggested by our HMI review study. Finally, any provided information can be model specific and updated after any updates to the automation.

Part III - Exploration and validation of a digital in-car tutor

Based on the previous studies, a Digital In-Car Tutor (DIT) was proposed at the start of Part III to support driver's understanding and appropriate use of car automation. Such a DIT gradually guides the driver in learning about, and trying out, the automated functions during regular driving trips. Although we proposed that such a DIT needs to be adaptive to the environment and the driver to facilitate optimal learning, there were no practical guidelines. The aim of our next study (**Chapter 6**) was therefore to gain inspiration for a DIT and investigate adaptive tutoring strategies in a real-world and driving related context. Additionally, we specifically examined whether and how the information may need to be adaptive to the complexity of the driving environment, as this may affect drivers workload and their ability to effectively process and understand the presented information. Driving instructors and their students were therefore video recorded during their regular driving lessons as this existing communication loop shows a similar dynamic as one would see between a DIT and a driver. In this metaphor, the DIT takes the role of the driving instructor. Both quantitative and qualitative analyses were conducted to identify natural feedback patterns of the instructors and their adaptivity to the driving environment and the students. The results show that instructors adapt the feedback length, level of detail and content type to the complexity of the driving situation to avoid overloading the driver. As the situation becomes more complex, the feedback becomes shorter, less detailed and more action oriented. Situations of lower complexity allow for longer, more detailed and theory driven feedback. Additionally, the feedback adapts to the driver's experience. During the initial use period, more elaborate information is necessary to form a basic understanding of the automation. For example, drivers without experience with the automation need more detailed information on why the automation is (capable of) performing a certain action. Additionally, the first use period requires more frequent repetition and practise of

the information.

In order to be able to conduct the observation study (Chapter 6) however, it was necessary to examine which elements of the driving situation actually determine its overall complexity. Although other studies have investigated the effect of one specific road- or traffic element, there was no condensed overview of elements which may contribute to the overall complexity when designing scenarios. In **Chapter 7**, we therefore first collected all infrastructure- and traffic characteristics that may influence the perceived complexity of a driving situation from literature. Next, four sets of driving scenarios of varying complexities were created. These were then rated on their complexity through an online survey. This study resulted in: 1) a list of infrastructure- and traffic characteristics that influence the overall complexity of a driving situation, and 2) validated scenarios of varying complexities. These outcomes can be used by researchers and designers in setting up future driving studies.

In **Chapter 8**, we developed an DIT prototype which was adaptive to (the complexity of) the driving environment, and conducted a driving simulator study to evaluate its effect on appropriate automation use. The study consisted of three sessions, each containing multiple driving scenarios. Participants needed to use the automation when they thought that it was safe, and turn it off if it was not. The control group read an information brochure before driving, while the experimental group received the DIT during the first driving session. The results showed more appropriate automation use, and better take-over quality, for users of the DIT during the first driving session. The DIT especially reduced inappropriate reliance behaviour, which is important to support traffic safety. Overall, the concept of an adaptive DIT shows potential as an efficient solution for safe guided learning in partially automated cars.

Final conclusions

This thesis reveals that drivers are currently insufficiently supported in understanding and appropriately using partially automated cars. It is crucial that immediate and thorough measures are taken to avoid a negative impact on both traffic safety and the adoption of car automation. Our research further shows that a Digital In-car Tutor that is adaptive to the (complexity of the) driving situation positively affects appropriate automation use. While additional research is necessary with regards to the practical implementation, this research provides a solid base for the improvement of in-car driver support aimed at helping drivers to understand and appropriately use their car's automation.