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Silvia Francesca Varotto

Delft University of Technology, 2018

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HUMAN FACTORS OF AUTOMATED DRIVING

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Driver Behaviour during Control Transitions between Adaptive Cruise Control and Manual Driving: Empirics and Models

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Nothing in life is to be feared, it is only to be understood.
Now is the time to understand more, so that we may fear less.

Marie Skłodowska-Curie

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Silvia
Palazzolo dello Stella, August 2018

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List of Acronyms and Abbreviations

A	‘Active’ state of Adaptive Cruise Control system
AAc	‘Active and Accelerate’ state of Adaptive Cruise Control system
Ac	‘Acceptable’ level of risk feeling and task difficulty
ACC	Adaptive Cruise Control
ADAS	Advanced Driver Assistance Systems
AIDC	‘Automation Initiates transition, and Driver Controls after’
AL	‘Active’ state of Adaptive Cruise Control system when the level of risk feeling and task difficulty is low
AS+	‘Active’ state of Adaptive Cruise Control system and increase the target speed
AS-	‘Active’ state of Adaptive Cruise Control system and decrease the target speed
ASM	Adaptive Smoothing Method
BC	Baseline Condition
BMW	Bayerische Motoren Werke
CAN	Controller Area Network
DBC	Driver behaviour characteristic
DIAC	‘Driver Initiates transition, and Automation Controls after’
DIDC	‘Driver Initiates transition, and Driver Controls after’
EC1	Experimental Condition 1
EC2	Experimental Condition 2
FOT	Field Operational Test
GDP	Gross Domestic Product
GPS	Global Positioning System
H	‘High’ level of risk feeling and task difficulty
HCM	Highway Capacity Manual
I	‘Inactive’ state of Adaptive Cruise Control system
L	‘Low’ level of risk feeling and task difficulty

LCW	Lane Change Warning
NS	Non-significant results
O	‘Off’ state of Adaptive Cruise Control system
RAT	Risk Allostasis Theory
RFTD	Risk feeling and task difficulty
RFTDE	Risk feeling and task difficulty evaluation
SAE	Society of Automotive Engineers
TOR	Take Over Request
TP	Transition period
TS+	Target speed increment in Adaptive Cruise Control
TS-	Target speed decrement in Adaptive Cruise Control

Chapter 1

Introduction

Automated vehicles and driving assistance systems such as Adaptive Cruise Control (ACC) are expected to reduce traffic congestion and accidents. Fields Operational Test (FOT) studies have showed that drivers may prefer to disengage ACC and resume manual control in dense traffic conditions and before changing lane. These control transitions between ACC and manual driving can significantly influence the longitudinal driver behaviour characteristics and are consequently expected to have an impact on traffic flow efficiency and safety.

This chapter introduces the current knowledge and the main challenges on driver behaviour during control transitions between ACC and manual driving, which represents the focus of this dissertation. The chapter is structured as follows. Section 1.1 introduces the problem statement. Section 1.2 presents the current knowledge on data collection methods suitable to analyse control transitions, empirical findings in driving simulator and on-road experiments, and models predicting driver choices to transfer control. Based on this overview, the research gaps and challenges are discussed in Section 1.3. Section 1.4 defines the research objectives and the research questions, and Section 1.5 the research scope. Section 1.6 describes the research approach, which comprises empirical studies describing driver behaviour characteristics during control transitions and choice models predicting drivers' decisions to resume manual control. The main scientific and practical contributions are discussed in Section 1.7. Finally, Section 1.8 outlines the contents of this dissertation.

1.1 Problem statement

The interactions between individual drivers, their vehicles and environmental conditions are the most important causes of traffic congestion and accidents on the freeway (Hamdar et al., 2015; Saifuzzaman and Zheng, 2014; Treiber and Kesting, 2013). Traffic congestion increases travel time, accident probability, and levels of emissions. These negative impacts result in considerable social and private costs. In Europe, road congestion costs 1% of the GDP per year (Christidis and Ibanez Rivas, 2012) and traffic accidents are one of the leading causes of death and injuries (World Health Organization, 2017). Hence, improving the efficiency and the safety of the road transport network are main priorities for policy makers.

According to the European Commission (2017), the introduction of cooperative, connected and automated vehicles can contribute to mitigate traffic congestion and accidents. Automated vehicles, in particular those that can show cooperative behaviour, may increase roadway capacity, improve traffic flow stability, and speed up the outflow from a queue (for a review, refer to Hoogendoorn et al. (2014)). In addition, automated vehicles are expected to mitigate traffic accidents by reducing driver error, which is responsible for the majority of collisions (International Transport Forum, 2015).

Automated driving systems can take over some or all of the driving tasks, based on their capabilities to sense the environment, process the data, and control the vehicle. The Society of Automotive Engineers International defines six levels of automation (SAE International J3016): manual driving (Level 0), driver assistance (Level 1), partial automation (Level 2), conditional automation (Level 3), high automation (Level 4), and full automation (Level 5). At the driver assistance level, the system takes over either the longitudinal or the lateral control. For example, Adaptive Cruise Control (ACC) is a driver assistance system providing support to the longitudinal control of the vehicle (acceleration and deceleration) through maintaining a target speed and time headway. In partial automation, the system takes over longitudinal and lateral control, while the driver permanently monitors the system and is expected to resume control at any time. In conditional automation, the system takes over longitudinal and lateral control, while the driver does not have to continuously monitor the system and is expected to resume control in case of an emergency (e.g., sensor failure). In high automation, the system takes over longitudinal and lateral control, even if the driver does not respond adequately to a request to intervene in case of certain roadway and environmental conditions. In full automation, the system full-time takes over longitudinal and lateral control under all roadway and environmental conditions. The driver is not required to monitor the system.

In certain traffic situations, drivers might prefer to transfer to a lower level of automation (or manual driving) (Viti et al., 2008) or the system transfers to a lower level of automation (or manual driving), for instance due to a sensor failure (Nilsson et al., 2013). These transitions between automation and manual driving are called *control transitions* (Lu et al., 2016). Control transitions can significantly influence the longitudinal and lateral driver behaviour characteristics (e.g., speed, acceleration, time headway, lane changes) and are consequently expected to have an impact on traffic flow efficiency (Klunder et al., 2009) and safety (Vlakveld et al., 2015). A primary concern is to understand driver behaviour with ACC, which represents the first level of vehicle automation and is currently available into the market. Control transitions can reduce the expected benefits of ACC on traffic flow efficiency, contributing to traffic flow instability, an increase in congestion levels and a slower clearance of congestion. In addition, drivers might show an impaired ability to respond to safety critical situations when resuming manual control. The first step towards predicting the impacts of control transitions between ACC and manual driving on traffic flow is to investigate driver behaviour during these transitions based on empirical data, which represents the focus of this dissertation. The insights and conclusions from this analysis are essential for the development of models describing driver behaviour during control transitions, which can be implemented into microscopic traffic flow simulations to predict the impact of these transitions on traffic flow efficiency.

1.2 State of the art on driver behaviour during control transitions between ACC and manual driving

Lu et al. (2016) defined control transitions as the process involving the *reallocation* of the lateral or the longitudinal control task between the automation and the driver. The authors introduced a framework to classify control transitions based on who (driver or automation) initiates the transition and who is in control afterwards. In this framework, transitions are defined as follows: 'Driver Initiates transition, and Driver in Control after' (DIDC) when drivers deactivate the system, 'Driver Initiates transition, and Automation in Control after' (DIAC) when drivers activate it, and 'Automation Initiates transition, and Driver in Control after' (AIDC) when the system disengages because of its operational limitations. Control transitions have a direct impact on the longitudinal and the lateral driver behaviour characteristics of the vehicle, and are consequently expected to have an impact on traffic flow efficiency and safety. To understand the situations in which control transitions occur and how drivers respond during these transitions, empirical data can be collected in driving simulator and on-road experiments. Based on these empirical data, mathematical models describing driver behaviour during control transitions can be developed. This section presents an overview of advantages and disadvantages of different data collection methods to analyse control transitions between ACC and manual driving (Section 1.2.1), empirical findings from driving simulator and on-road experiments (Section 1.2.2), and driver behaviour models that describe control transitions and are suitable for implementation into microscopic traffic flow simulations (Section 1.2.3).

1.2.1 Data collection methods for driving behaviour during control transitions

Data collection methods for empirical driver behaviour differ in terms of controllability and external validity (for a review, refer to Anund and Kircher (2009)). Controllability can be defined as the ability to control for confounding factors in the experiment, while external validity is defined as the ability to generalize the findings to real life. Data collection methods that offer a high degree of controllability often result in a relatively low level of external validity. The most suitable data collection method should be chosen based on the specific research question and safety precautions (e.g., testing a novel driving assistance system and safety critical traffic situations).

Driving simulators allow researchers to present exactly the same driving scenarios to all the participants (De Winter et al., 2006). The virtual environment and the simplified driving scenarios can result in a reduction in validity. However, findings in Yan et al. (2008) suggest that driving simulator studies possess relative validity, which means that the observed behavioural response takes place in the same direction but not with the same magnitude as in real life. The main advantages of driving simulator studies over on-road studies are the following: possibility of controlling the traffic situations under investigation, of proposing exactly the same traffic situations to all participants and to the same participant multiple times, and of guaranteeing participants' safety in critical traffic situations. The main disadvantage of this method is the limited external validity, meaning that the findings may only be generalized to real life situations with caution.

On-road studies provide researchers with a unique possibility of analysing driving behaviour in real traffic and measuring driver response with a high degree of external validity. These studies may be classified into three groups (for a comprehensive review, refer to Carsten et al. (2013)): controlled on-road studies, Field Operational Tests (FOTs), and naturalistic driving studies. Controlled on-road studies consist of limited experiments on a pre-set route designed to answer specific research questions, while FOTs and naturalistic studies are large-scale experiments focusing respectively on the evaluation of a certain treatment (e.g., a new driving assistance system or a training program) and the diagnosis of regular driving behaviour (e.g., investigating the causes of pre-crash events) (Carsten et al., 2013). The main advantages of controlled on-road studies compared to the other two are the possibility of controlling for confounding factors (e.g., road design, traffic flow conditions, time of the day and weather), increasing the exposure to the conditions under investigation (e.g., congestion), and accommodating an observer in the test vehicle. The main disadvantage of this method is a possible reduction in external validity due to the controlled nature of the experiment (e.g., the presence of the observer might influence drivers' behaviour).

Driver behaviour during control transitions can be analysed in both driving simulator and on-road studies. In the field of human factors, driver behaviour with ACC has been mainly investigated in driving simulator experiments (Nilsson, 1995; Saffarian et al., 2012; Stanton and Young, 2005; Stanton et al., 1997; Strand et al., 2014; Ward et al., 1995). In these experiments, driver response to AIDC transitions can be analysed in a safe and highly controllable environment. In the field of transportation engineering, driver behaviour with ACC systems that are inactive at low speeds has been investigated in FOTs (NHTSA, 2005; Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008; Viti et al., 2008). These experiments focused on the usage of the ACC system in real traffic, analysing the conditions in which control transitions occur and changes in the mean driver behaviour characteristics before and after the control transitions. However, findings from these driving simulator and on-road experiments suffer from limitations that are related to the experimental design and the data collection method. Results from these studies will be discussed in the next section.

1.2.2 Empirics of driving behaviour during control transitions

The ACC system assists drivers in maintaining a target speed and time headway and therefore has a direct adaptation effect on the longitudinal control task (Martens and Jenssen, 2012). The influence of the ACC on driver behaviour has been extensively analysed since the 1990s, mainly in driving simulator experiments. Some driving simulator studies have found a reduction in situation awareness (Stanton and Young, 2005) and very low levels of self-reported mental workload (Saffarian et al., 2012) while driving with ACC. ACC systems that automatically regulate the speed when the vehicle approaches the leader may result in higher speeds and shorter time headways when they are active (Dragutinovic et al., 2005; Ward et al., 1995). On-road experiments have shown that, when the ACC is active, drivers maintain larger time headways (Alkim et al., 2007; Malta et al., 2012; NHTSA, 2005; Schakel et al., 2017), follow the leader twice as long as in manual driving (NHTSA, 2005), spend more time in the middle and left lane (fast lane) and prepare lane changes in advance to anticipate possible interactions with slower vehicles (Alkim et al., 2007). These results, however, might be influenced by the conditions in which the ACC system is activated (e.g., medium-high speeds, light-medium traffic and non-critical conditions).

Driving simulator studies have analysed drivers' response to AIDC transitions in safety critical situations with a high level of controllability. ACC systems which have functioning limitations may lead to more collisions than unsupported driving, for instance when drivers have to resume manual control to avoid collision while approaching a stationary queue (Nilsson, 1995) and when the system fails by accelerating unexpectedly towards the vehicle in front (Stanton et al., 1997). In case of deceleration failures with ACC, the mean reaction time of drivers varies between 1.60 s and 2.26 s, depending on the magnitude of the deceleration failure (Strand et al., 2014).

On-road studies have analysed traffic situations in which drivers transfer control and possible adaptations in mean driver behaviour characteristics after manual control is resumed. Field Operational Tests (FOTs) have suggested that, with ACC systems that are inactive at speeds lower than 30 km/h, DIDC transitions happen before manoeuvres such as lane changing (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008) and in dense traffic conditions at speeds 50-70 km/h (NHTSA, 2005; Viti et al., 2008). After the ACC system is deactivated, the mean time headway and the mean acceleration decrease significantly (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008). AIDC transitions occur because of the operational limitations of the system in a safety-critical situation or a sensor failure. Recently, ACC systems that operate at low speeds in stop-and-go conditions (full-range ACC) have been introduced into the market. These ACC systems might be activated and deactivated in different situations and result in different adaptation effects. A controlled on-road study showed that, with full-range ACC, DIDC transitions occur when the vehicle exited the freeway, approached a moving vehicle and changed lane, and when the leader changed lanes or a vehicle cut in (Pereira et al., 2015). However, this study did not analyse potential adaptation effects in the driver behaviour characteristics after manual control was resumed.

In summary, FOTs have shown significant changes in the mean driver behaviour characteristics before and after control transitions with ACC systems that are inactive at low speeds (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008). The mean values of the driver behaviour characteristics aggregated over 10-s intervals in a wide range of traffic situations were compared (before vs. after control transitions) using repeated measures analysis of variance (ANOVA). These changes in driver behaviour characteristics can be interpreted as adaptation effects and need further investigation. The approach proposed, however, does not quantify the duration of these adaptation effects explicitly and does not control for the impact of potentially confounding factors. In addition, the studies reviewed suggest that the circumstances in which control transitions occur are related to the characteristics of the driver support system, the drivers themselves, the road, and the traffic flow. To analyse the impact of all these factors on drivers' choices to transfer control, mathematical models should be developed based on empirical data.

1.2.3 Modelling decisions of control transitions

In on-road experiments, only one or a few research vehicles equipped with a driving assistance system are tested at a time. Therefore, the impact of different system penetration rates on traffic operations (e.g., 50% of the vehicles on the road are equipped with the system) cannot be directly assessed. For this purpose, mathematical models of vehicles equipped with the system can be developed and implemented into microscopic simulation software packages. In these traffic simulators, the traffic dynamics (speed and position) of individual driver-vehicle units are reproduced by using car-following and lane-changing models (for recent reviews, refer to Saifuzzaman and Zheng (2014) and Zheng (2014)). Traffic simulation studies have suggested that ACC has a positive impact on traffic flow efficiency when it is active in dense traffic (Van Driel and Van Arem, 2010). However, most of the models currently used to evaluate the impact of ACC do not describe control transitions.

A few mathematical models (Klunder et al., 2009; Van Arem et al., 1997; Xiao et al., 2017) have proposed deterministic decision rules for transferring control, based on a sequence of assumptions made by the modellers and empirical findings at an aggregate level. Drivers activate the ACC system when the speed and the acceleration fall within the range supported by the system and deactivate when the vehicle changes lane, approaches a considerably slower leader, and brakes hard. Notably, the parameters were not formally estimated. Inconsistencies in the decision-making process, heterogeneity between and within drivers, and interdependencies between different levels of decision making have been ignored. Therefore, the ability of these models to reproduce the actual decision-making process of drivers needs further investigation.

To capture interdependencies between different driver behaviours and heterogeneity within and between drivers in the decision-making process, previous studies have proposed modelling frameworks based on discrete choice models. These models have been primarily used to predict the probability that drivers change lanes based on vehicle trajectory data (Ahmed et al., 1996; Choudhury et al., 2007; Toledo et al., 2003), data collected in an on-road experiment (Sun and Elefteriadou, 2014), and driving simulator data (Farah and Toledo, 2010). Discrete choice models are suitable for implementation into a microscopic traffic flow simulation because each individual is modelled independently. These models are flexible from a behavioural point of view, provide statistical techniques to capture complex error structures, and facilitate a rigorous estimation of the model parameters. The main advantages compared to alternative methods (e.g., artificial intelligence) are that the model structure can be selected based on insights from driver control theories and that the estimation results are directly interpretable.

A few studies have proposed conceptual models for drivers' choices to transfer control in ACC and have estimated the probability that drivers transfer control, using discrete choice models based on empirical data. Driver behaviour at an operational level (i.e., lateral and longitudinal control of the vehicle in the classification proposed by Michon (1985)) have been studied in driver control theories. The most widely accepted driver control theory is the Risk Allostasis Theory (RAT) proposed by Fuller (2011). The RAT argues that driver control actions are primarily informed by the desire to maintain the feeling of risk and task difficulty within an acceptable range. Inspired by this theory, Xiong and Boyle (2012) proposed a conceptual model of driver behaviour in ACC including initiating (actual risk) and mediating factors (perceived risk). They estimated a mixed logit model with panel effect to predict the probability that drivers would brake to initiate a DIDC transition as they closed in on a leader. Results showed that drivers are more likely to deactivate the ACC in non-highway environments, at lower speeds, and with short time headway settings. Young drivers (20-30 years old) were less likely to resume manual control than middle-aged drivers (40-50 years old). Notably, this study predicts transitions to manual control with an ACC system that is inactive at low speeds only when the system automatically brakes. The possibility of adapting the ACC system settings (speed and time headway) to regulate the longitudinal control task was ignored. The research gaps and challenges on understanding and modelling driver behaviour during control transitions are detailed in the next section.

1.3 Research gaps and challenges on driver behaviour during control transitions

To date, limited efforts have been made to study and model control transitions between full-range ACC and manual driving in a way that would be suitable for implementation into microscopic traffic simulation models. Based on the state of the art in Section 1.2, two main research gaps are identified as follows:

Research gap 1: the duration and magnitude of adaptations in driver behaviour characteristics during control transitions between full-range ACC and manual driving remain unclear;

Research gap 2: a conceptual framework and a flexible mathematical model that predict driver choices to transfer control with ACC are missing.

To address the first research gap, the main challenges are the following:

Challenge 1: designing driving simulator and on-road experiments that are suitable to understand driver behaviour during control transitions;

Challenge 2: analysing adaptations in driver behaviour characteristics when drivers resume manual control.

To address the second research gap, the main challenges are designing suitable experiments **(Challenge 1)** and

Challenge 3: developing a modelling framework based on theories of driver psychology to predict driver choices to transfer control.

The first challenge is to design driver simulator and on-road experiments that are suitable to determine the influence of AIDC, DIAC and DIDC transitions on the longitudinal driver behaviour characteristics (speed, acceleration, distance headway, and relative speed). As described in Section 1.2.1, driver behaviour during control transitions between ACC and manual driving has been analysed in both driving simulator and on-road studies. However, most driving simulator studies were conducted in the field of human factors and focused on drivers' reaction times in AIDC transitions. Findings in these studies cannot be easily generalized to real traffic situations due to the virtual environment, the oversimplified driving scenarios, and a sample of participants that did not represent the driving population. FOTs have analysed driver behaviour with ACC systems that are inactive at low speeds. These studies gained limited insights into the situations in which DIAC and DIDC transitions occur and potential adaptations in the driver behaviour characteristics due to lack of control for potential confounding factors. Very few on-road studies have analysed ACC systems that are active at low speeds in stop and go conditions (Pereira et al., 2015). In summary, new driving simulator and on-road experiments should be designed to better understand driver behaviour during control transitions with full-range ACC systems.

The second challenge is to develop statistical analysis techniques to capture adaptations in driver behaviour characteristics when drivers resume manual control. As described in Section 1.2.2, few studies have analysed changes in the mean driver behaviour characteristics before and after the control transitions (values aggregated over 10-s intervals) using a repeated measures ANOVA (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008). However, limited insight was gained on the duration of these adaptation effects because the 10-s intervals were chosen arbitrarily and any temporal evolution of the driver behaviour characteristics over these time intervals was ignored. It is not clear whether variations in the mean driver behaviour characteristics occur in medium-dense traffic flow conditions, which are more relevant to understand impacts on traffic efficiency and safety. In addition, these studies did not control for the confounding effect of any additional control transitions initiated within these time intervals, when the system was deactivated or overruled by pressing the gas pedal for less than 10 s. To control for these factors, a more in-depth analysis using flexible statistical methods is needed.

The third challenge is to develop a modelling framework based on theories developed in the field of traffic psychology to predict drivers' choices to transfer control. As described in Section 1.2.3, a few microscopic traffic flow simulations have proposed deterministic decision rules for transferring control, disregarding inconsistencies in the decision-making process, heterogeneity between and within drivers, and dependencies between different levels of decision making. These models were not supported by current theories of driver behaviour and were not estimated based on empirical data. Few studies have proposed a conceptual framework for control transitions based on theories developed in driver psychology (Fuller, 2011) and have analysed the factors influencing control transitions using discrete choice models estimated based on empirical data (Xiong and Boyle, 2012). However, the model proposed is limited to situations in which the subject vehicle approaches a slower leader. In summary, limited efforts have been made to develop a comprehensive conceptual framework for driver behaviour with ACC at an operational level and to propose a flexible mathematical formulation for this modelling framework. The research objectives and the research questions addressing these challenges are detailed in the next section.

1.4 Research objectives and research questions

The main objectives of this thesis, addressing the challenges presented in Section 1.3, are defined as follows:

Objective 1 (Challenge 2): to describe adaptations in driver behaviour characteristics during control transitions between full-range ACC and manual driving;

Objective 2 (Challenge 3): to develop a mathematical model that predicts driver choices to transfer control and to regulate the ACC target speed grounded on driver control theories.

To achieve these objectives, empirical data are collected in driver simulator and on-road experiments that are suitable to analyse the influence of AIDC, DIAC and DIDC transitions on the longitudinal driver behaviour characteristics (speed, acceleration, distance headway, and relative speed) and the situations in which drivers initiate control transitions **(Challenge 1).**

To gain insights into adaptations in driver behaviour characteristics during control transitions **(Objective 1)**, two research questions should be answered as follows:

Research question 1: How do drivers behave when full-range ACC deactivates because of a sensor failure?

Research question 2: How do driver behaviour characteristics change over time after the full-range ACC is deactivated or overruled by pressing the gas pedal?

To develop a model framework that predicts drivers' choices to transfer control and to regulate the ACC target speed **(Objective 2)**, the following research questions should be answered:

Research question 3: What factors (driver behaviour, driver, and road characteristics) influence drivers' decisions to resume manual control in full-range ACC?

Research question 4: How to model drivers' decisions to resume manual control and to regulate the target speed in full-range ACC?

The first research question focuses on drivers' time to resume control and driver behaviour characteristics when the system deactivates because of a sensor failure (AIDC transitions) and when the system can be re-activated after the sensors are functioning again (DIAC transitions). To answer this research question, driver behaviour data are collected in a driving simulator experiment and analysed using descriptive statistics **(Objective 1)**. The second research question focuses on adaptations in driver behaviour characteristics after the ACC system is deactivated or overruled by pressing the gas pedal (DIDC transitions). This research question is answered collecting driver behaviour data in an on-road experiment and developing appropriate data analysis techniques **(Objective 1)**. The third research question focuses on identifying the factors that influence drivers' decision to deactivate the system or overrule it by pressing the gas pedal. The fourth research question focuses on developing a mathematical model that predicts drivers' choices to deactivate the system or overrule it by pressing the gas pedal, and to increase or decrease the target speed. These research questions are answered developing choice models **(Objective 2)** based on the data collected in the on-road experiment. The research scope of this thesis is defined in the next section.

1.5 Research scope

This thesis focuses on driver behaviour during control transitions between manual driving and a full-range ACC system that is active at low speeds in stop and go conditions. The full-range ACC represents the first level of vehicle automation and has been recently introduced into the market. Thus, the system can be safely tested on the road in open traffic with non-expert drivers. In addition, drivers who own a vehicle equipped with the ACC can be recruited as participants in the experiment to gain insights into its long-term use. Notably, the methods proposed in this thesis can be extended to study driver behaviour with higher levels of automation.

This thesis analyses the impact of control transitions between full-range ACC and manual driving on drivers' longitudinal control of the vehicle. This level of the driving task (operational level) is directly influenced by the functioning of the system, which supports drivers in their longitudinal control by maintaining a desired speed and time headway. The tactical level (manoeuvres such as overtaking and gap acceptance) of the driving task and the strategical level (general planning of the trip) are not investigated. The thesis focuses on understanding driver response in regular driving conditions with ACC, when the driver is expected to monitor the environment and does not engage in non-driving tasks. The statistical analysis methods capturing adaptations in driver behaviour characteristics and the choice models predicting control transitions are applied only to transitions from full-range ACC to manual driving. However, the data analysis methods developed can also be extended to model transitions from manual driving to full-range ACC. In this thesis, driver behaviour is measured by the driver behaviour characteristics which are relevant to develop a microscopic traffic flow model (e.g., speed, acceleration, distance headway, and relative speed). The driver state is not monitored using physiological measurements. The findings in this thesis contribute to the design of new driver assistance systems which are acceptable to drivers in a wider range of traffic situations. However, controllers for these new systems are not directly developed.

The road environment consists of freeway mainline with two (or more) lanes per direction, separate carriageways, and no at-level intersections. The road environment in the driving simulator experiment reproduces a Dutch freeway. The on-road experiment is conducted on the A99 freeway in Munich (Germany). On the freeway mainline, the driving speed can range from zero kilometres/hour in congested traffic to the speed limit (if present) in free-flow conditions. The subject vehicle equipped with the ACC interacts with other individual vehicles driven manually. In these experiments, vehicle to vehicle communications and vehicle to infrastructure communications are not considered and vulnerable road users such as pedestrians and cyclists are not present. This freeway environment represents the primary environment where full-range ACC have been designed to operate in. The results in this thesis shed light on the potential impacts of this system on traffic flow efficiency in the short term. However, evaluating the impact of control transitions on traffic flow efficiency and safety at a network level is beyond the scope of the current thesis. The research approach proposed is discussed in the next section.

1.6 Research approach

The main research objectives are achieved by developing mathematical models describing driver behaviour during control transitions with full-range ACC based on empirical data. The novelty of this research approach is in collecting empirical data that are useful to understand driver behaviour characteristics during control transitions, and in developing mathematical models that allow a rigorous model estimation capturing variability between and within drivers.

The general approach of understanding driver behaviour during control transitions between ACC and manual driving and predicting the impact of these transitions on traffic flow efficiency and safety is presented in Figure 1.1. This thesis focuses on acquiring driver behaviour data during control transitions and on analysing these data using statistical analysis methods. The data were collected both in driving simulator and in on-road experiments to investigate the conditions in which control transitions happened and to understand drivers' response when manual control was resumed. These data collection methods are characterised by different levels of validity and controllability. The data analysis methods comprise empirical analyses and choice models. The driver behaviour data collected in the experiments were analysed using descriptive statistics and statistical analysis methods to identify potential adaptions in driver behaviour characteristics (speed, acceleration, distance headway, and relative speed) during control transitions. Choice models were developed to model drivers' decisions to transfer control and to regulate the target speed based on the Risk Allostasis Theory (RAT), which is one of the most widely accepted theories explaining driver behaviour at an operational level (Fuller, 2011). These models were fully estimated using the data collected and can be implemented into microscopic traffic flow simulations to predict the impact of control transitions on traffic operations. An overview of the research approach proposed is described in the following sections.

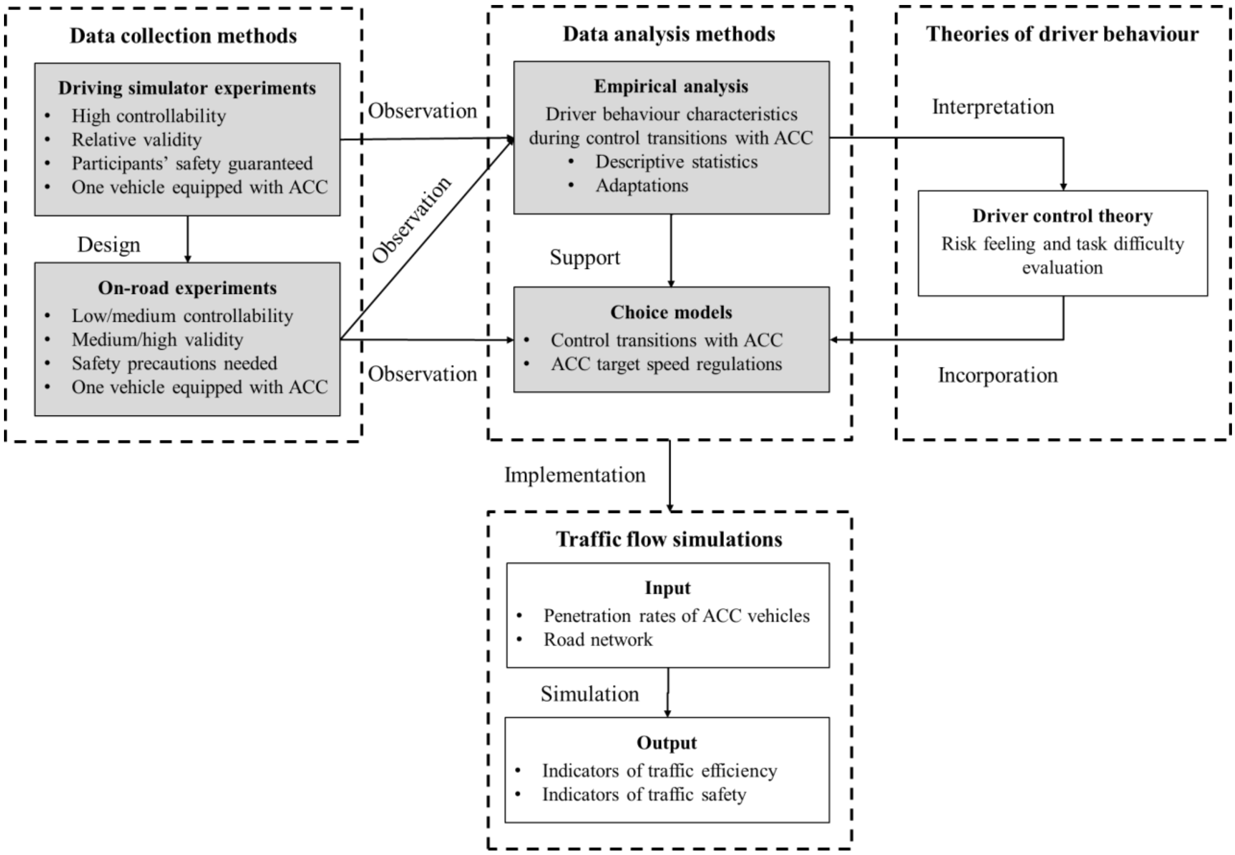


Figure 1.1: Process of understanding and modelling driver behaviour during control transitions between full-range ACC and manual driving.

Note: The grey boxes indicate the research phases that are addressed in this thesis.

1.6.1 Empirics of driving behaviour during control transitions

The first phase of this research aimed at understanding drivers' response during control transitions. This phase focused on describing the driver behaviour characteristics before the full-range ACC system is activated and after it is deactivated. For this purpose, a driving simulator experiment was carried out.

The influence of control transitions initiated by the ACC system (AIDC transitions after sensor failure) and by drivers (DIAC and DIDC transitions) on the driver behaviour characteristics were analysed in a controlled driving simulator experiment (Chapter 2). This data collection method allows presenting the same traffic flow and environmental conditions to all participants with a high degree of controllability and a minimal safety risk. These are clear advantages when analysing infrequent events and safety critical situations. In this experiment, a sensor failure was simulated at a specific location where drivers were expected to resume manual control. The driver behaviour characteristics during control transitions were analysed by using descriptive statistics and statistical tests at an aggregate level.

This experiment showed that control transitions have a significant impact on the driver behaviour characteristics. If the speed drop during control transitions was confirmed in reality, control transition could reduce the expected benefits of full-range ACC in mixed traffic conditions. Further analysis was needed to investigate driver behaviour characteristics when drivers deactivated the ACC discretionary. For this purpose, a controlled on-road experiment was carried out.

Potential adaptations in driver behaviour characteristics when drivers resume manual control (DIDC transitions) were analysed in an on-road experiment with full-range ACC on a pre-set route (Chapter 3). This data collection methodology allows controlling for confounding factors such as road design and traffic flow conditions, which are expected to influence driver behaviour. This dataset was used in the remainder of the thesis. Linear mixed-effects models were estimated to identify (statistically) the duration and magnitude of changes in the driver behaviour characteristics when drivers resume manual control. These models allow analysing the impact of several within-subjects factors simultaneously (time period, traffic density, and ACC system state) on the driver behaviour characteristics, capturing between-subjects variations and correlations between observations over time for the same driver.

1.6.2 Modelling decisions of control transitions

The second phase of this research aimed at modelling the circumstances in which drivers resume manual control (DIDC transitions). The empirical findings in the previous phase indicate that drivers may differ in their choices to activate and to deactivate the ACC system in similar traffic situations. We hypothesized that drivers might be influenced in their decisions by their personal characteristics, the driver behaviour characteristics of the subject vehicle and of the direct leader, and by the characteristics of the road. A study based on empirical data accounting for all these factors in a wide range of traffic situations is currently missing.

The factors that influence drivers’ decisions to deactivate the system or overrule it by pressing the gas pedal were analysed in a mixed logit model (Chapter 4). This model allows analysing the impact of several within-subjects factors simultaneously (driver behaviour, driver and road characteristics) on the repeated choices of individual drivers over time, capturing between-subjects variations (panel effect).

The results showed that control transitions in full-range ACC are determined by the factors that influence risk feeling and task difficulty evaluations in driver control theories. To date, limited efforts have been made to develop a comprehensive conceptual framework for driver behaviour with ACC and to propose a flexible mathematical formulation for this modelling framework. To regulate the longitudinal control task, drivers can resume manual control or regulate the ACC target speed. The magnitude of the ACC target speed regulation influences these choices. To capture interdependencies between different driver behaviours, a comprehensive modelling framework for control transitions and target speed regulations is needed.

A choice modelling framework describing drivers’ decisions to transfer control and to regulate the ACC target speed was developed based on the Risk Allostasis Theory and the empirical findings in the previous phase (Chapter 5). Drivers choose to resume manual control or to regulate the ACC target speed (binary logit and regression models) if the perceived level of risk feeling and task difficulty falls outside the range considered acceptable to maintain the system active (ordinal probit model). In this framework, the magnitude of the ACC target speed regulation is chosen simultaneously to the system state and correlations between these two choices are captured explicitly. A driver-specific error term captures unobserved heterogeneity which affects all choices made by individual drivers. These models can be implemented into a microscopic simulation to assess the impact of ACC on collective flow operations accounting for control transitions and target speed regulations.

1.7 Main contributions

This section presents an overview of the main contributions of this thesis. These contributions are described as follows. Section 1.7.1 focuses on the contributions to the scientific literature, while Section 1.7.2 focuses on the contributions to practice.

1.7.1 Scientific contributions

Conceptual model for driver decisions to resume manual control and to regulate the target speed in full-range ACC based on Risk Allostasis Theory (Chapter 5). This conceptual model represents one of the first attempts to develop a framework explaining driver interaction with Advanced Driving Assistance Systems (ADAS) at an operational level based on theories developed in the field of driver psychology. In this framework, the perceived risk feeling is influenced by the driver behaviour characteristics of the subject vehicle and of the leader. The acceptable range with the ACC active varies between drivers and within drivers over time, being influenced by driver characteristics, by the functioning of the system, and by the environment. The decisions to resume manual control or to regulate the target speed in high (or low) risk situations are influenced by the driver behaviour characteristics, by the functioning of the system, by environmental conditions, and by driver characteristics. This conceptual model contributes to an improved understanding of the relations between the explanatory variables that influence driver behaviour with full-range ACC and supports the estimation of mathematical models that capture interdependencies between different decisions.

Choice model predicting transitions to manual control and target speed regulations in full-range ACC (Chapter 5). To the best of the author's knowledge, this is the first mathematical model predicting both transitions to manual control and target speed regulations in full-range ACC in a wide range of traffic situations. The model explicitly recognizes the ordinal and discrete nature of the underlying risk feeling and task difficulty evaluation. The mathematical formulation proposed accommodates decisions on both discrete and continuous variables, modelling unobservable constructs, inconsistencies in drivers' decision making that might be caused by human factors, and interdependencies between decisions in terms of causality, unobserved driver characteristics, and state dependency. The model allows to investigate the impact of different explanatory variables on each level of decision making and to quantify the impact of changes in these variables on drivers' decisions to transfer control and to regulate the target speed. The model parameters can be rigorously estimated based on empirical data using maximum likelihood methods.

Maximum likelihood estimation of the choice model based on-road data with full-range ACC (Chapter 5). This one of the first attempts to estimate a mathematical model for control transitions based on driver behaviour data. The maximum likelihood method guarantees a rigorous estimation of the model parameters capturing complex error structures. Using this estimation method, it is possible to test statistically the impact of different explanatory variables on each level of decision making, underpinning empirically the conceptual model proposed.

Identification of transition period and corresponding adaptation in the driver behaviour characteristics after drivers resume manual control in full-range ACC using linear mixed-effects models (Chapter 3). To the best of the author's knowledge, this is the first study that identifies statistically significant changes in the mean driver behaviour characteristics over time a few seconds after drivers deactivated or overruled the ACC based on data collected in an on-road experiment. This statistical analysis method captures the impact of several observable factors and interdependencies between repeated observations over time for the same driver. The significant speed reductions (or increments) can be interpreted as a compensation strategy to decrease (or increase) the feeling of risk and task difficulty. Therefore, the insights support the conceptual model proposed for control transitions.

Insights on drivers' time to resume control and driver behaviour characteristics when the full-range ACC deactivates because of a sensor failure and when the system can be re-activated after the sensors are functioning again (Chapter 2). This is one of the first studies that analyse driver behaviour characteristics during control transitions in a driving simulator experiment with a high degree of controllability. In addition, very few studies have analysed the time needed by drivers to re-activate the system after a sensor failure. The changes in driver behaviour characteristics identified point towards the relevance of developing traffic flow models that mimic driver behaviour during control transitions.

Empirical driver behaviour data with full-range ACC collected in driving simulator (Chapter 2) *and in on-road experiments* (Chapter 3). Driver behaviour data from sixty-seven participants were collected in the driving simulator experiment to analyse driver response to a sensor failure in full-range ACC with a high level of safety and controllability. Findings in this study offer a deeper insight into driver behaviour in real traffic situations thanks to a realistic driving scenario and a sample of participants that represents the driving population. Driver behaviour data from twenty-three participants were collected in the on-road experiment to analyse driver behaviour during DIDC transitions with a high degree of validity and controlling for potential confounding factors such as road design and traffic conditions. This is one of the few on-road studies available in literature that investigates ACC systems active at low speeds. Besides the analysis and modelling of control transitions presented in this thesis, the data collected can be used to investigate other aspects of driver behaviour with full-range ACC.

Current knowledge on empirics and models of driver behaviour during control transitions between ACC and manual driving. Driver behaviour during control transitions between ACC and manual driving has been analysed in driver simulator and on-road experiments. Few studies have proposed conceptual frameworks and mathematical models for control transitions that can be implemented in microscopic traffic flow models. However, a critical overview of these empirical findings and mathematical models is currently missing. This overview points towards the relevance of designing new experiments and acquiring new data to better understand driver behaviour during control transitions. These empirical data should be analysed using advanced statistical methods and interpreted based on driver control theories to gain insights that are useful to improve the realism and accuracy of current mathematical models. The review proposed in this thesis focuses on the following topics:

- Advantages and disadvantages of driving simulator and on-road experiments to analyse driver behaviour during control transitions (Chapter 2 and Chapter 3);
- Potential reasons for control transitions between ACC and manual driving (Chapter 2);

- Adaptations in driver behaviour characteristics before the ACC is activated and after it is deactivated (Chapter 3);
- Statistical analysis methods for adaptations in driver behaviour that capture the impact of observed and unobserved factors (Chapter 3);
- Mathematical models predicting the circumstances in which control transitions occur in ACC (Chapter 4);
- Driver control theories and conceptual models of adaptations in driver behaviour (Chapter 5);
- Integrated driver behaviour models that capture interdependencies between different driving behaviours (Chapter 5).

1.7.2 Practical contributions

Main factors influencing drivers' decisions to resume manual control and to regulate the target speed in full-range ACC (Chapter 4 and Chapter 5). Based on the data collected in the on-road experiment, this thesis provides one of the first comprehensive assessments of the main factors influencing drivers' choices to deactivate the ACC, to overrule the system by pressing the gas pedal, and to increase or to decrease the target speed using choice models. The models show that the driver behaviour characteristics, the driver characteristics, the functioning of the system, and the environment influence driver decisions with ACC. These factors should be accounted for when developing new ADAS and when evaluating the impact of these systems on traffic operations.

Empirical foundation for increasing the human likeness of ADAS. The findings in this thesis provide valuable guidance to human factors experts and automotive engineers for designing new ADAS that can anticipate drivers' responses and adapt their settings to prevent control transitions. The controllers of these human-like ADAS should include factors such as the driver behaviour characteristics, the driver characteristics, the functioning of the system, and the environment. The choice model can be directly implemented to identify the situations in which drivers are likely to resume manual control in full-range ACC (Chapter 5). In these situations, the system can be programmed to increase or decrease the target speed similarly to the responses of human drivers (Chapter 3). ADAS designed based on these empirical findings are expected to be acceptable for drivers in a wider range of traffic situations.

Empirical foundation for increasing the realism of microscopic traffic flow models that describe driver behaviour during control transitions between full-range ACC and manual driving. The results have shown that there are large differences between and within drivers in the same traffic situation, which can be explained by the functioning of the system, observed and unobserved driver characteristics, and environmental conditions. Therefore, all these factors should be included into microscopic traffic flow models describing driver behaviour during control transitions. The choice model based on risk feeling and task difficulty (Chapter 5) can be directly implemented into a simulation package and is expected to result in more accurate predictions than the models available, which account for a limited number of explanatory factors and are based on deterministic decision rules. In addition, a car-following model grounded on risk feeling and task difficulty can be developed to capture explicitly the adaptations in driver behaviour characteristics described in Chapter 2 and Chapter 3. In this model, the vehicle acceleration can be specified explicitly as a function of two additive terms, the first one representing regular car-following behaviour and the second one representing adaptations during control transitions. Implementing this advanced car-following model into a microscopic traffic flow simulation, the impact of transitions from ACC to manual control on capacity, capacity drop and string stability can be investigated more realistically than in current traffic flow simulations.

1.8 Outline of the dissertation

The dissertation outline and the links between the chapters are presented in Figure 1.2. Chapter 2 and Chapter 3 present the empirical analyses of driver behaviour characteristics during control transitions. Chapter 2 analyses the influence of control transitions initiated by the ACC system and by drivers on the driver behaviour characteristics in a controlled driving simulator experiment. Chapter 3 describes potential adaptations in driver behaviour characteristics in an on-road experiment with full-range ACC. This dataset was used in the remainder of the thesis. Chapter 4 and Chapter 5 propose choice models predicting the circumstances in which drivers transfer control. Chapter 4 analyses the factors that influence drivers' decision to deactivate the system or overrule it by pressing the gas pedal in a mixed logit model. Based on the empirical insights in Chapter 4 and current theories of driver behaviour, Chapter 5 presents a continuous-discrete choice modelling framework describing drivers' decisions to resume manual control and to regulate the ACC target speed. Chapter 6 discusses the main research findings, potential impacts of control transitions on traffic flow efficiency, and recommendations for future research.

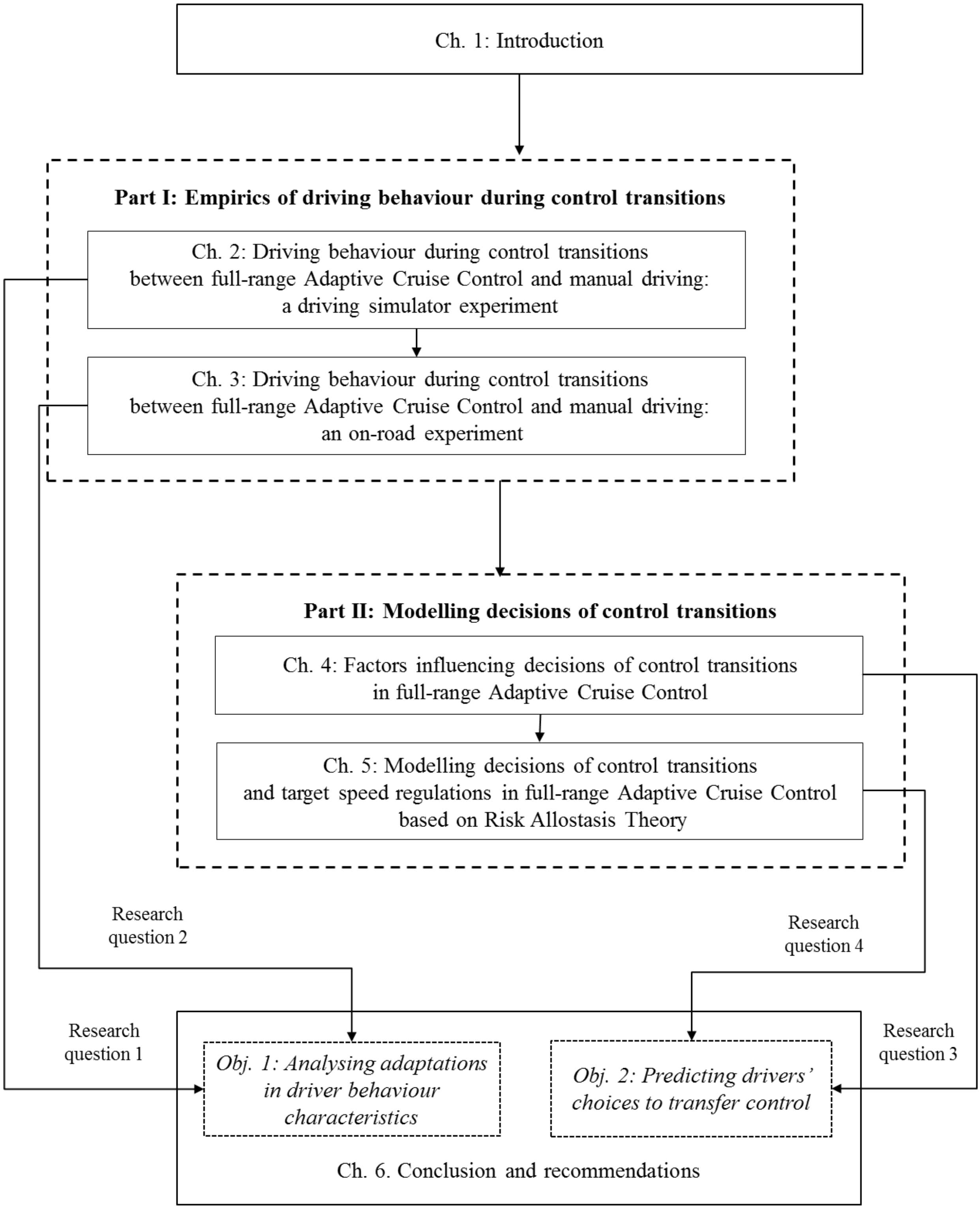


Figure 1.2: Overview of the dissertation structure (including the relationships between chapters, the research objectives and the research questions addressed in each chapter).

I Empirics of driving behaviour during control transitions

Chapter 2

Driver behaviour characteristics during control transitions between full-range Adaptive Cruise Control and manual driving: a driving simulator experiment

The FOT studies reviewed in Chapter 1 have showed that drivers may prefer to disengage ACC and resume manual control in dense traffic conditions and before changing lane. Moreover, the ACC can disengage because of sensor failures or system support constraints reached. These control transitions are expected to have substantial effects on the driver behaviour characteristics. However, limited insight into these effects was gained in the FOT studies found because potentially confounding factors could not be precisely controlled for.

This chapter analyses the influence of control transitions initiated by the ACC system (AIDC transition after sensor failure) and by drivers (DIAC and DIDC transitions) on speed, acceleration, and time headway in a controlled driving simulator experiment. The chapter is structured as follows. Section 2.1 introduces driver behaviour during control transitions and Section 2.2 reviews possible reasons for control transitions. Section 2.3 presents the driving simulator experiment, which comprises three conditions (manual driving, experimental condition with AIDC and DIAC transitions, and experimental condition with DIAC and DIDC transitions). Section 2.4 describes the results of the experiment in-depth through statistical analyses. Section 2.5 discusses the influence of control transitions on longitudinal driver behaviour characteristics and presents the limitations of the proposed approach, while also suggesting recommendations for future research.

This chapter is an edited version of the following paper:

Varotto, S.F., Hoogendoorn, R.G., Van Arem, B., Hoogendoorn, S.P., 2015. Empirical longitudinal driving behavior in authority transitions between Adaptive Cruise Control and manual driving. *Transportation Research Record: Journal of the Transportation Research Board* 2489, 105-114.

https://doi.org/10.3141/2489-12

NOTE: The terminology and the references used in the original paper have been revised based on more recent studies.

2.1 Introduction

In recent years, interest in automated vehicles and systems supporting the drivers in their control task has increased. Automated vehicles are expected to have a significant impact on traffic flow efficiency, safety levels and the environment. These vehicles, in particular those that can show cooperative behaviour, are expected to reduce congestion levels because they will help to increase road capacity, anticipate traffic conditions downstream and increase the outflow from a queue (Hoogendoorn et al., 2014).

The introduction of automated vehicles on public roads is likely to be gradual: the functionalities of automated systems are introduced through intermediate steps. The Society of Automotive Engineers International defines the different levels of automation as follows (SAE Standard J3016):

Level 0: manual driving,
Level 1: driving assistance,
Level 2: partial automation,
Level 3: conditional automation,
Level 4: high automation,
Level 5: full automation.

At the driving assistance level, the system takes over either the longitudinal or the lateral control. For example, Adaptive Cruise Control (ACC) is a driver assistance system providing support in longitudinal control through maintaining a desired speed and time headway. In partial automation, the system takes over longitudinal and lateral control, while the driver permanently monitors the system and is expected to resume control at any time. In conditional automation, the system takes over longitudinal and lateral control, while the driver does not have to continuously monitor the system and is expected to resume control in case of an emergency (e.g., sensor failure). In high automation, the system takes over longitudinal and lateral control, even if the driver does not respond adequately to a request to intervene in case of certain roadway and environmental conditions. In full automation, the system full-time takes over longitudinal and lateral control under all roadway and environmental conditions. The driver is not required to monitor the system.

Under certain traffic situations, however, drivers might disengage the automated system because they prefer to transfer to a lower level of automation (or manual driving) (Viti et al., 2008) or are forced to do so, for instance due to a sensor failure (Nilsson et al., 2013). These transitions between different levels of automation are called control transitions. These transitions can significantly affect the longitudinal and lateral driver behaviour characteristics of vehicles and are consequently expected to have a considerable impact on traffic flow efficiency (e.g., traffic flow stability).

To ex ante evaluate the impact of automated vehicles on traffic flow efficiency at varying penetration rates, mathematical models of driving behaviour of manually driven and automated vehicles can be implemented in microscopic simulation software packages (Kesting et al., 2008; Klunder et al., 2009). Currently, most mathematical models describing car-following and lane-changing behaviour do not account for the possibility to switch the automated system on and off and are therefore not adequate in representing these transitions. Thus, an extension of these models is required. However, in order to do so, a better understanding is needed of how control transitions affect the lateral and longitudinal driver behaviour characteristics of vehicles.

The aim of this research is to provide insight into the theory and empirics of longitudinal driving behaviour during control transitions between ACC and manual driving. The main contribution of this paper is to explore the effects of control transitions on the longitudinal driver behaviour characteristics through extensive statistical analyses of data obtained in a driving simulator experiment. Participants were asked to drive in a vehicle equipped with ACC on a virtual two-lane freeway using a medium fidelity fix-based driving simulator at Delft University of Technology. Speed, acceleration, distance and time headway, lateral position and lane changes were measured through registered behaviour. In a baseline condition, participants were required to drive manually. In the first experimental condition, a sensor failure was simulated at a specific location after which the driver was required to resume manual control over the vehicle. In the second experimental condition, the drivers were allowed to switch the system off and on voluntarily.

2.2 Literature review

Before investigating the effects of control transitions on the longitudinal driver behaviour characteristics, it is essential to discuss the possible motivations that trigger the transitions. Section 2.2.1 proposes possible reasons for control transitions between ACC and manual driving based on available literature. Section 2.2.2 introduces an overview of the available research on behavioural adaptations and the changed role of the driver with ACC to explore the potential effects of control transitions on driving behaviour. Section 2.2.3 discusses potentialities and limitations of data collection methods such as Field Operational Tests (FOTs) and driving simulator experiments.

2.2.1 Driver and automation initiated control transitions with ACC

The control transitions appear to be strongly related to the characteristics of the driver support system. These transitions can be initiated by the driver voluntary or by the automated system because of its own functioning limitations. For example, FOTs (Viti et al., 2008) investigated driving behaviour with types of ACC systems that have limited decelerations capabilities and are inactive at speed below 30 km/h. Drivers preferred to disengage ACC and resume manual control during dense traffic conditions in order to have smaller distance headways. In medium–dense traffic conditions, drivers tended to deactivate the system to have full control of the vehicle (e.g., in case of overtaking manoeuver).

Lu et al. (2016) defined control transitions as ‘Driver Initiates transition, and Driver in Control after’ (DIDC) when drivers resume manual control and ‘Driver Initiates transition, and Automation in Control after’ (DIAC) when drivers engage the system. The most common motivations to initiate a DIDC transition with the above-mentioned types of ACC are presented below (Klunder et al., 2009; Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008):

- *Speed adaptation prior to a lane change manoeuver:* the driver plans to make a lane change and the current acceleration is not adequate;
- *Overruling due to defensive or offensive behaviour:* the driver brakes (or accelerates) to create a sufficient (or insufficient) gap for a vehicle in an adjacent lane for merging;
- *Left-lane speed adaptation*: the driver brakes to avoid illegal overtaking on the right and to adapt to the speed of the vehicle in the adjacent lane.

Lu et al. (2016) defined control transitions as ‘Automation Initiates transition, and Driver in Control after’ (AIDC) when the driver support system disengages because of its own functioning limitations. Possible reasons for AIDC transitions with the above-mentioned types of ACC are presented below (Klunder et al., 2009; Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008):

- *A sensor failure:* the sensor cannot work properly (e.g., poor visibility due to adverse weather conditions) and the driver has to resume manual control;
- *Reaching the system support constraints in a safety-critical situation:* the system support constraints in speed and acceleration are reached; however, the driver needs to exceed these limits in order to avoid collision or overtake.

2.2.2 Behavioural adaptations and changed role of the driver with ACC

Adaptations in driving behaviour are defined as the collection of behavioural aspects that arise following a change in road traffic (Martens and Jenssen, 2012). For instance, the influence of ACC systems activated on the longitudinal driving behaviour of drivers has been extensively investigated since the 1990s. Similarly, there has been an interest in Automated Highway System (AHS) which takes over the longitudinal and lateral control of vehicles driving in an automated lane (Levitan et al., 1998).

Driving simulator studies have suggested that ACC systems that have functioning limitations may lead to more collisions than unsupported driving, for instance when the drivers have to resume manual control because the deceleration is not sufficient to avoid collision while approaching a stationary queue (Nilsson, 1995) and the system fails accelerating unexpectedly towards the vehicle in front (Stanton et al., 1997). Recently, a driving simulator study pointed out that in case of deceleration failures with ACC the mean reaction time of drivers varies between 1.60 s and 2.26 s, depending on the magnitude of the deceleration failure, and concluded that humans are poor monitors of automation (Strand et al., 2014). Driving simulator studies have also investigated the transfer of control between the AHS and the driver of a vehicle entering and exiting an automated lane (Levitan and Bloomfield, 2014). In the latter, drivers were warned 60 s in advance before exiting the automated lane, resuming manual control and changing lane. The authors concluded that these transitions resulted in an unacceptable rate of incomplete lane changes and collisions. In addition, driving simulator studies have suggested that ACC systems, which automatically regulate the speed when the vehicle gets too close to the leader, may result in higher speeds and shorter time headways when they are active (Dragutinovic et al., 2005; Ward et al., 1995). Different results were found in a driving simulator study that tested a system controlling speed, time headway and lateral position inside the lane (Bloomfield et al., 1998). Drivers were allowed to set a preferred speed and time headway using a switch. When the automated system was used, the speed did not noticeably change while the time headway increased. After the system was disengaged in light traffic conditions, the mean speed decreased while the mean time headway increased for young drivers and decreased for old drivers. However, little attention has been paid to the influence of driver and automation initiated control transitions as defined above on the longitudinal driver behaviour characteristics of vehicles and the behavioural adaptations of drivers.

The effects of ACC on driving behaviour may be related to the changed role of the driver, who is transformed from a manual controller to a supervisor of the system (Hoogendoorn et al., 2014). Indeed, automated vehicles require drivers who are capable to resume control during control transitions. Studies in the field of aviation have suggested that monitoring the system for long periods of time might increase the workload of the driver (Parasuraman et al., 1996), which can result in a reduction in situation awareness and a failure in the detection of critical changes in the state of the system (Ephrath and Young, 1981). In addition, indirect adaptation effects may be caused by over-reliance on the system, which is defined as the tendency of human supervisors to place too much trust in automated systems (Danaher, 1980). In the road transport field, some driving simulator studies have found a similar reduction in situation awareness (Stanton and Young, 2005) and very low levels of self-reported mental workload (Saffarian et al., 2012) while driving with ACC.

2.2.3 Data collection methods

The validity of data collected in a FOT can be considered relatively high while the level of controllability is limited (Anund and Kircher, 2009). Indeed, in a FOT it is not possible to present exactly the same conditions to all the participants and therefore precisely control for potential confounding variables. Vice-versa, driving simulators possess a high degree of controllability. Presenting exactly the same traffic flow and environmental conditions to all the participants, driving performances can be objectively assessed (De Winter et al., 2006). Since reality is represented virtually, driving simulator experiments can result in a reduction in validity. However, findings from Yan et al. (2008) suggest that driving simulator studies possess relative validity, which means that the observed behavioural response converges in the same direction but not with the same magnitude as in real life.

The studies found point out that drivers may prefer to disengage ACC and resume manual control for many traffic situations (e.g., dense traffic conditions, lane change manoeuver, gap creation, left-lane speed adaptation) (Klunder et al., 2009; Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008; Viti et al., 2008). Moreover, the system can switch off due to sensor failure or system support constraints reached. These studies were based on data collected in a FOT. In addition, ACC is assumed to reduce driver's vigilance and situation awareness. Therefore, we may conclude that ACC can compromise driver's ability to respond in case of emergency situations and sensor failure. Most of the studies on the changed role of the driver in relation to automation were performed using driving simulator studies or were conducted in the field of aviation. On the basis of the current literature, a driving simulator experiment is missing that analyses the influence of the above-defined driver and automation initiated control transitions on the longitudinal driver behaviour characteristics of vehicles and the behavioural adaptations of drivers. Given the importance of understanding this transitional process and its implications on driving behaviour, this research focuses on acquiring such data.

2.3 Research method

This study aims at gaining in-depth insight into driving behaviour in control transitions through a driving simulator experiment. The main objective is to analyse to what extent control transitions between ACC and manual driving affect the driver behaviour characteristics of vehicles. The behavioural assumption to test is that the control transitions between ACC and manual driving cause significant changes in speed, acceleration and time headway. In addition, the variation in drivers' responses during driver and automation initiated control transitions is explored. To study this, an experiment with a high degree of controllability is used.

Section 2.3.1 describes the driving simulator and the driving environment designed for the purpose of this study. Section 2.3.2 discusses the experimental design. Section 2.3.3 presents the data collected to approximate the longitudinal driving behaviour and a description of the participants.

2.3.1 The driving simulator and the driving environment

A medium-fidelity fixed-based driving simulator, which is shown in Figure 2.1 *a*, was used in the experiments. This simulator was chosen because of availability reason. The simulator is composed of a steering wheel, pedals and gear stick, which were obtained from a real car. Three screens placed at an angle of 120° show outside world images, the dash-board, the interior of the vehicle and the mirrors. The simulator provides a visual field of view of 180° horizontally and 45° vertically. The software was developed by StSoftware™ (Van Wolffelaar and Van Winsum, 1992). The gearbox was set to automatic.

For this experiment, a driving environment was implemented composed of two main parts (7 km in total). The first part consisted of a test run (2 km) in an urban environment. In this phase, all the participants drove manually and the use of ACC was not possible. The aim was to accustom the participants to driving in the driving simulator and check for simulator sickness. The second part, which is shown in Figure 2.1 *b*, consisted of two segments (2 km each) of a virtual freeway with two lanes in each direction, connected by a one lane stretch (1 km). In this research, only the data collected in the two freeway segments were analysed. The speed of the surrounding vehicles was programmed to vary randomly in the intervals 80 to 85 km/h and 110 to 115 km/h in the right lane, and 120 to 125 km/h in the left lane. These vehicles changed lane when the speed of their leader was lower than their own speed. When ACC was switched on, the speed was set to 120 km/h (i.e., the speed limit) and the time headway was set to 1.5 s, without any possibilities to regulate the system settings. The ACC was active in a full speed range and had the same deceleration limitations as manual driving.

(a) (b)

Figure 2.1: (a) The medium-fidelity fixed-based driving simulator and (b) the driving simulation environment in the two-lane freeway.

2.3.2 Experimental design

The experiment consisted of a control condition and two experimental conditions, making up a *complete three group independent samples randomized experimental design*. The driving environment and the characteristics of the surrounding vehicles were exactly the same for each condition. In the baseline condition (BC), control transitions were not possible *by definition* and the participants had to drive manually. In the first experimental condition (EC1), ACC was switched on automatically after merging into the freeway and the drivers were informed by a message on the screen (‘ACC is switched on’). On the second stretch of the freeway, a sensor failure was simulated at a predefined location and the system automatically disengaged by decelerating the vehicle. The driver was warned by a message on the screen (‘Sensor failure!’) and was expected to resume manual control. The response of the system was designed to avoid safety-critical situations in case of sensor failure. At the next location, another message appeared on the screen (‘Sensors are ok!’) after which it was possible to switch ACC on again. In the second experimental condition (EC2), the drivers were allowed to switch ACC off and on by using a button on the dashboard whenever they desired.

2.3.3 Participants and data collection

The participants were assigned randomly to one of the above-mentioned groups. Seventy-five participants were recruited among the male and female inhabitants of Delft between the ages of 20 and 72 years old. A valid driving license and more than one year of driving experience were considered as a prerequisite.

Before the experiment, participants received written instructions on the general scope of the research, the features of the driving simulator and the potential risks related to simulator sickness. Participants were asked to drive as in real life and allowed to overtake. In addition, they were informed on the characteristics of the ACC available and warned to monitor the system and be able to resume manual control at any time. However, the precise scope of the experiment (i.e., analysing driving behaviour in control transitions) was not communicated. After that, a written informed consent was signed. The whole procedure was executed following the regulations of the ethics committee of Delft University of Technology.

The duration of the experiment varied between 8 and 20 minutes, depending on the participants. After that, participants completed a questionnaire in which they reported demographic characteristics, driving experience, previous experience with cruise control or ACC in real life, information related to driving styles and mental workload experienced. Eight participants were not able to complete the experiment due to simulator sickness. Statistics regarding the characteristics of the participants who successfully completed the experiment are reported in Table 2.1. The analysis of the full questionnaire is not included due to space limitations. The two-sample Kolmogorov-Smirnov test was performed to determine whether the three groups came from the same population. The null hypothesis that the distributions of the variables gender, age, driving experience, previous experience with cruise control or ACC in real life and previous experience with driving simulator in the three groups came from the same distribution could not be rejected at the 5% significance level. This means that the distributions of these variables do not differ significantly between the three groups. The test statistics are presented in Table 2.2.

Table 2.1: Statistics on participants' characteristics in the baseline condition (BC), the experimental condition 1 (EC1) and the experimental condition 2 (EC2)

Characteristics	BC (N=25)	EC1 (N=21)	EC2 (N=21)
Gender (n_{male}, n_{female})	14, 11	15, 6	12, 9
Age (M_{years}, SD_{years})	47.08, 15.05	38.10,11.82	39.19, 13.18
Driving experience (M_{years}, SD_{years})	24.72, 13.05	19.38, 11.49	21.55,14.18
Experience with cruise control or ACC in reality ($n_{exp.}$, $n_{inexp.}$)	7, 18	6, 15	11, 10
Experience with driving simulator ($n_{exp.}$, $n_{inexp.}$)	3, 22	2, 19	4, 17

Table 2.2: Kolmogorov-Smirnov tests on participants' characteristics in the baseline condition (BC), the experimental condition 1 (EC1) and the experimental condition 2 (EC2)

Two-sample Kolmogorov-Smirnov test	BC – EC1		BC – EC2		EC1 – EC2	
	p-value	Test Statistic	p-value	Test Statistic	p-value	Test Statistic
Gender *(female)*	0.93	0.15	1.00	0.01	0.89	0.17
Age *(years)*	0.07	0.37	0.19	0.31	0.83	0.19
Driving experience *(years)*	0.11	0.34	0.57	0.22	0.87	0.17
Experience with cruise control or ACC in reality *(experienced)*	1.00	0.01	1.00	0.01	0.45	0.24
Experience with driving simulator *(experienced)*	1.00	0.02	1.00	0.07	0.99	0.09

Note: Comparison of BC with EC1 and EC2, and of EC1 with EC2. *Female* is a variable which is equal to 1 when the participant is a female and 0 otherwise. *Experienced* is a variable which is equal to 1 when the participant has previous experience and 0 otherwise.

Longitudinal driving behaviour was measured through registered data in the driving simulator. Speed, acceleration, distance and time headway, lateral position and lane changes were measured at a sampling rate of 10 Hz. Sixty-seven complete observations were collected and analysed in this study.

2.4 Data analysis method

Section 2.4.1 analyses the distributions of speed, acceleration and time headway to study the longitudinal driver behaviour characteristics of vehicles during control transitions between ACC and manual driving. The behavioural hypothesis tested is that control transitions between ACC and manual driving can cause significant changes in speed, acceleration and time headway. Section 2.4.2 investigates the characteristics of driver and automation initiated control transitions in EC1, in terms of time needed to resume control and the consequent speed variation. Section 2.4.3 presents a detailed analysis of the driving behaviour of two single drivers in EC1. Here, control transitions are investigated by using a relative speed-spacing plane.

2.4.1 Analysis of speed, acceleration and time headway distributions

The outputs of the driving simulator were processed for each participant and the values of the driver behaviour characteristics speed, acceleration and time headway (rear bumper of the leader – front bumper of the follower) were calculated every two meters. For each location, the mean and the standard deviation of the driver behaviour characteristics were calculated between the participants in each condition. The distributions are plotted in Figure 2.2.

The mean and the standard deviation of the speed, acceleration, and time headway calculated as a function of distances in each condition are presented in Table 2.3. A one-sample Kolmogorov-Smirnov test was performed to check whether the mean and standard deviation of the driver behaviour characteristics are normally distributed. The null hypothesis that the distributions of the mean and standard deviation of speed, acceleration and time headway are normally distributed was rejected at the 5% significance level. After that, the two-sample Kolmogorov-Smirnov test was performed in order to understand whether the mean and standard deviation of the driver behaviour characteristics are homogenous between the three groups. The null hypothesis that the mean and standard deviation of speed, acceleration and time headway in the three groups came from the same distribution was rejected at the 5% significance level. The p-values and the test statistics are reported in Table 2.4. The results indicate that the longitudinal driver behaviour characteristics of the vehicles differ significantly between the three conditions. The largest difference in speed and time headway can be found between the BC and the EC1.

The driver behaviour characteristics in the BC were compared with the driver behaviour characteristics in the EC2. In Figure 2.2 *a*, the speed distributions seem to be similar in terms of mean and standard deviation. This result appears to be consistent with findings by Klunder et al. (2009). In the first segment of freeway, the mean and the standard deviation are generally constant over the distances in the BC, while the mean speed progressively increases and the standard deviation decreases in the EC2. These results seem to be consistent with the fact that more drivers switched ACC on over time. In Figure 2.2 *b*, the mean acceleration distributions are similar in both conditions. However, higher standard deviations can be noted where it was possible to switch ACC on and off and therefore the variability between drivers was higher. In Figure 2.2 *c*, the mean and standard deviation of time headway distributions in the EC2 are generally smaller and clearly decrease over distance in the first segment. This can be interpreted as an adaptation effect related to switching ACC on and off.

The driver behaviour characteristics in the EC1 were compared with the driver behaviour characteristics in the BC and in the EC2. In Figure 2.2 *a*, the mean speeds are higher and standard deviations are lower in the first segment where ACC is switched on and control transitions are not possible. After the sensor failure, it is important to note a significant drop in speed and increase in the standard deviation of speed, as a result of the different responses of drivers. A second drop in speed can be recognized after the message that informed the drivers that ACC could be switched on again. In Figure 2.2 *b*, significant changes in mean values of acceleration can be noted during the control transitions. In Figure 2.2 *c*, small mean time headways can be observed in the first segment of the freeway, while higher mean values can be found in the second segment. Indeed, the time headways increase after sensor failure, reaching values higher than these observed during manual driving after the sensors were functioning again and thus it was possible to switch ACC on voluntary. Interestingly, the latter result appears to be consistent with findings by Pauwelussen and Minderhoud (2008) and Pauwelussen and Feenstra (2010) in a FOT. In relation to this, the authors concluded that control transitions between ACC and manual driving might have a negative effect on traffic flow efficiency.

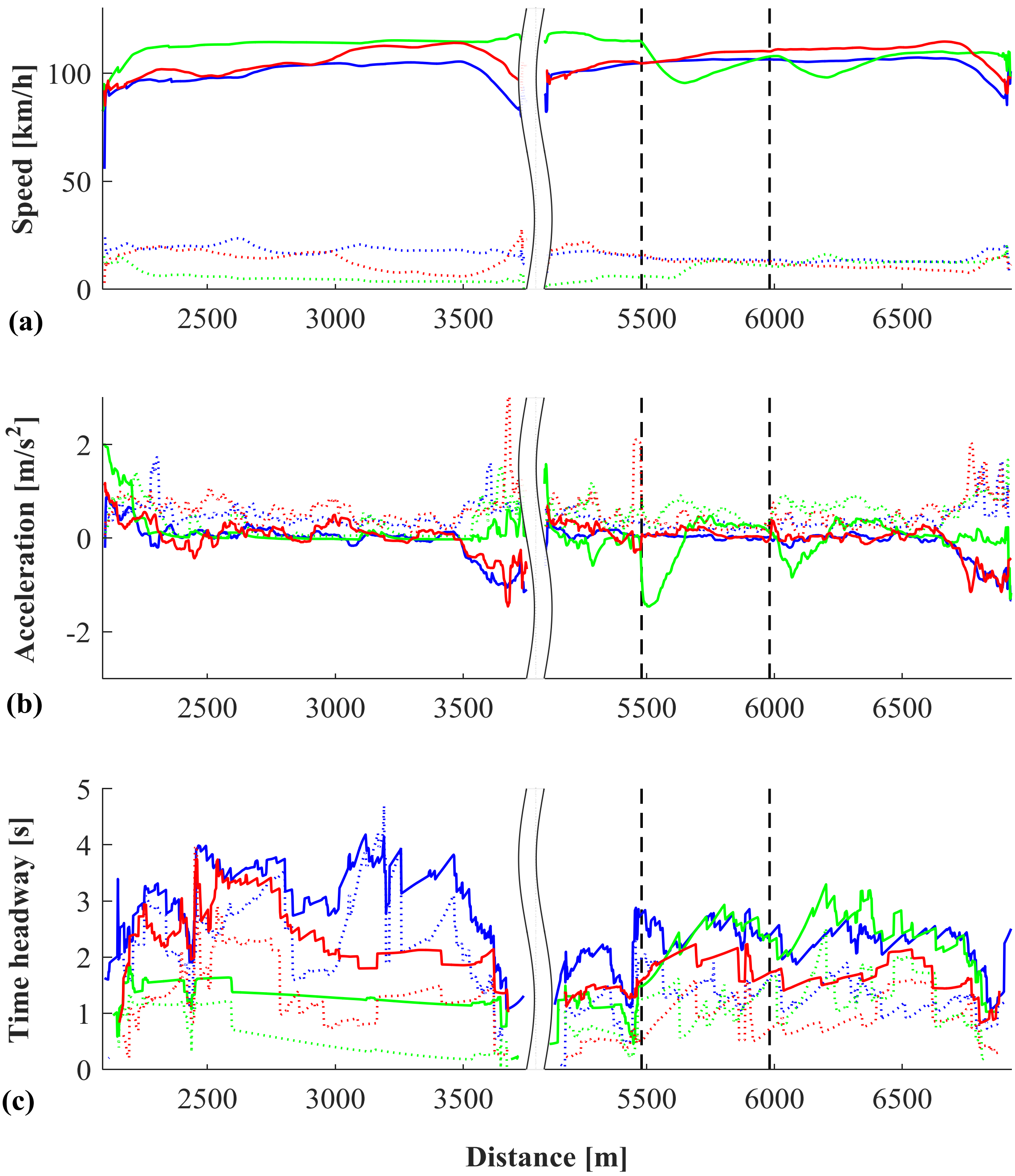


Figure 2.2: Mean (solid line) and standard deviation (dashed line) of (a) speed, (b) acceleration and (c) time headway distributions calculated as a function of the distance travelled since the beginning of the simulation for the baseline condition (blue), the experimental condition 1 (green) and the experimental condition 2 (red).

Note: The curve lines separate the first and the second segment of the freeway. For each segment, drivers entered and exited the freeway through on and off-ramps. The first dashed black line (distance=5480 m) indicates the location where sensor failure is simulated. After sensor failure, drivers were expected to resume manual control. The second dashed black line (distance=5981 m) indicates the location after which it was possible to switch ACC on again.

Table 2.3: Statistics on speed, acceleration and time headway distributions calculated as a function of the distance travelled in the first and the second segment of freeway for the baseline condition (BC), the experimental condition 1 (EC1) and the experimental condition 2 (EC2)

	Speed (km/h)			Acceleration (m/s^2)			Time headway (s)		
	BC	*EC1*	*EC2*	*BC*	*EC1*	*EC2*	*BC*	*EC1*	*EC2*
Mean of mean values over distances									
First segment	99.86	113.13	105.09	-0.02	0.16	0.03	3.07	1.30	2.36
Second segment	104.22	107.25	108.10	-0.06	-0.03	-0.01	2.21	2.10	1.66
Overall	102.15	110.05	106.67	-0.04	0.06	0.01	2.62	1.72	1.99
Mean of std. dev. values over distances									
First segment	18.59	5.28	13.65	0.50	0.31	0.62	2.43	0.60	1.38
Second segment	14.28	10.29	12.71	0.38	0.58	0.51	1.27	1.15	0.88
Overall	16.33	7.91	13.16	0.44	0.45	0.56	1.81	0.89	1.12

Note: In EC1, the sensor failure is simulated in the second segment of highway.

Table 2.4: Two sample Kolmogorov-Smirnov tests on speed, acceleration and time headway distributions calculated as a function of the distance travelled in the first and the second segment of freeway for the baseline condition (BC), the experimental condition 1 (EC1) and the experimental condition 2 (EC2)

	Speed (km/h)			Acceleration (m/s^2)			Time headway (s)		
	BC-EC1	*BC-EC2*	*EC1-EC2*	*BC-EC1*	*BC-EC2*	*EC1-EC2*	*BC-EC1*	*BC-EC2*	*EC1-EC2*
Mean of mean values over distances									
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Test statistic	0.73	0.51	0.73	0.17	0.19	0.11	0.53	0.51	0.39
Mean of std. dev. values over distances									
p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Test statistic	0.78	0.41	0.52	0.27	0.26	0.27	0.48	0.41	0.22

Note: Comparison of BC with EC1 and EC2, and of EC1 with EC2.

2.4.2 Analysis of control transitions in case of sensor failure (EC1)

In this section, the time to resume control and the resulting speed variation during control transitions are analysed for each participant *n* in the EC1. The sensor failure triggers an automation initiated control transition between ACC and manual driving (AIDC). After that, the possibility to reactivate ACC can lead to a driver initiated control transition between manual driving and ACC (DIAC).

AIDC transition

The time necessary to resume manual control $T_{RMC,n}$ in case of AIDC transitions is defined as the interval between the instant of sensor failure $T_{SFL,n}$ and the instant when the gas pedal is pressed again $T_{GPP,n}$. The distribution of $T_{RMC,n}$ is presented in Figure 2.3. Assuming that T^* is the median value of $T_{RMC,n}$, the median of the speed variation distribution ΔV_n that occurs during the control transition is calculated as follows in equation (2.1):

$$\Delta V = \text{median}\left(V_n^* - V_{SFL,n} \right), \tag{2.1}$$

where V_n^* is the speed at the instant T^* for each participant *n,* and $V_{SFL,n}$ is the speed at the instant of the sensor failure for each participant *n*.

DIAC transition

The time necessary to resume automatic control $T_{RAC,n}$ in case of DIAC transition is defined as the interval between the instant when the sensors are functioning again $T_{SFC,n}$ and the instant when ACC is switched on again by pressing the button $T_{ACC\ ON,n}$. The distribution of $T_{RAC,n}$ is presented in Figure 2.3. Two participants did not switch ACC on after the sensors were functioning again. The speed variation distribution ΔV_n is calculated similarly as described in equation (2.1).

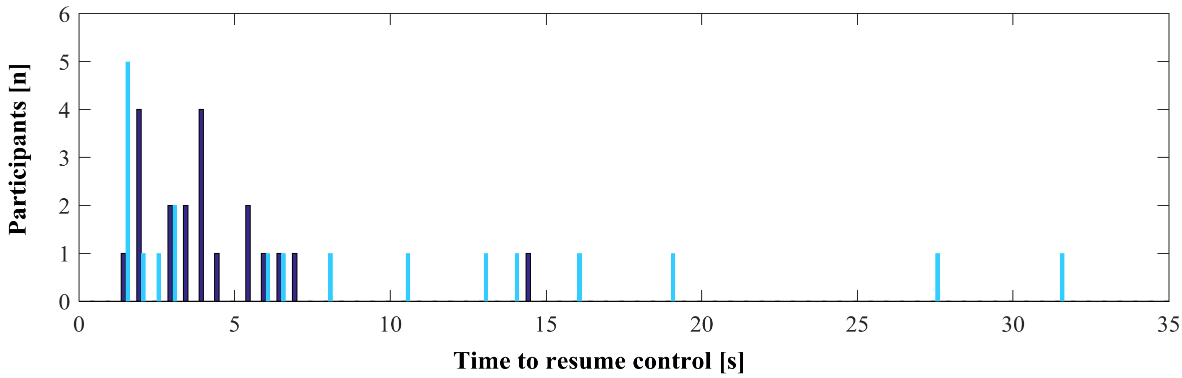


Figure 2.3: Time to resume manual control $T_{RMC,n}$ after sensor failure (blue) and time to resume automatic control $T_{RAC,n}$ after sensors were functioning again (light blue).

Statistics on the speed variation ΔV_n, the time to resume manual control $T_{RMC,n}$ and automatic control $T_{RAC,n}$ are reported in Table 2.5. The minimum time to resume control is lower in case of DIAC transition. However, the DIAC transition results in a higher median value of time to resume control due to the larger variability in the response of drivers. In the experiment, the AIDC transition always implies a negative speed variation because of the design of the driver support system, while the DIAC transition can lead to a positive or negative speed variation, depending on the response of the drivers. It is interesting to note that in both cases these transitions result in a negative median speed variation. If this speed drop was confirmed in reality, control transitions would potentially have considerable effects on traffic flow and reduce the expected benefits of ACC in mixed traffic conditions.

Table 2.5: Statistics on the distributions of time to resume control and speed variation during control transition in EC1

	Time to resume control (s)			Speed variation (km/h)		
	min	max	median	min	max	median
AIDC control transition	1.70	14.50	3.85	-20.37	-8.34	-18.18
DIAC control transition	1.40	31.40	5.80	-26.00	5.42	-4.22

2.4.3 Analysis of longitudinal driver behaviour characteristics of single drivers (EC1)

In this section, the longitudinal driver behaviour characteristics of two individual drivers (Driver 1 and Driver 2) in the EC1 are analysed in detail. The aim is to confirm and examine in-depth the general results found for the whole sample. In Figure 2.4 *a–b* speed, acceleration and time headway distributions are calculated as a function of distance travelled since the beginning of the simulation. In addition, the relative speed $dv = v_{i-1} - v_i$ to the leader *i-1* and the distance headway $s = x_{i-1} - x_i$ (rear bumper of the leader – front bumper of the follower) are calculated and plotted in a *(dv, s)* plane in Figure 2.4 *c–d*. When no leader was present, the data were discarded. In these *(dv, s)* planes, four different phases are distinguished following the definitions proposed in the previous section:

1. ACC before sensor failure (Driver 1 and Driver 2),
2. AIDC control transition (Driver 1 and Driver 2),
3. Manual driving after resuming control (Driver 1 and Driver 2),
4. ACC after DIAC control transition (Driver 2).

Constant acceleration periods could be clearly recognized. The duration of these periods is not fixed but is related to the state of the follower in relation to the leader. It can be assumed that the transitions between the different phases correspond to an action of the follower who wants to increase or decrease the acceleration. When the driver uses the ACC, periods of constant relative distance can be identified. The system tends to reduce the relative speed to zero. Here, discontinuities in the plots correspond to changes in the leader and consequently rapid variations in the acceleration. After the sensor failure, the vehicles decelerate uniformly and the relative speeds increase, until the drivers resume control and start to press the gas pedal again. When the vehicle is driven manually, an oscillation of the vehicle motion around states with a relative velocity equal to zero can be recognized (Leutzbach, 1988). It is interesting to note that these oscillations cannot be identified during control transitions and with ACC, which reacts to small speed differences. Driver 1 did not switch on again ACC after resuming control. When Driver 2 decided to switch ACC on again, the relative speed and distance headway increased compared to ACC before sensor failure, meaning that the gap to the leader increased in space and speed. These significant changes in driving behaviour seem to be related to control transitions and should be further investigated through on-road experiments.

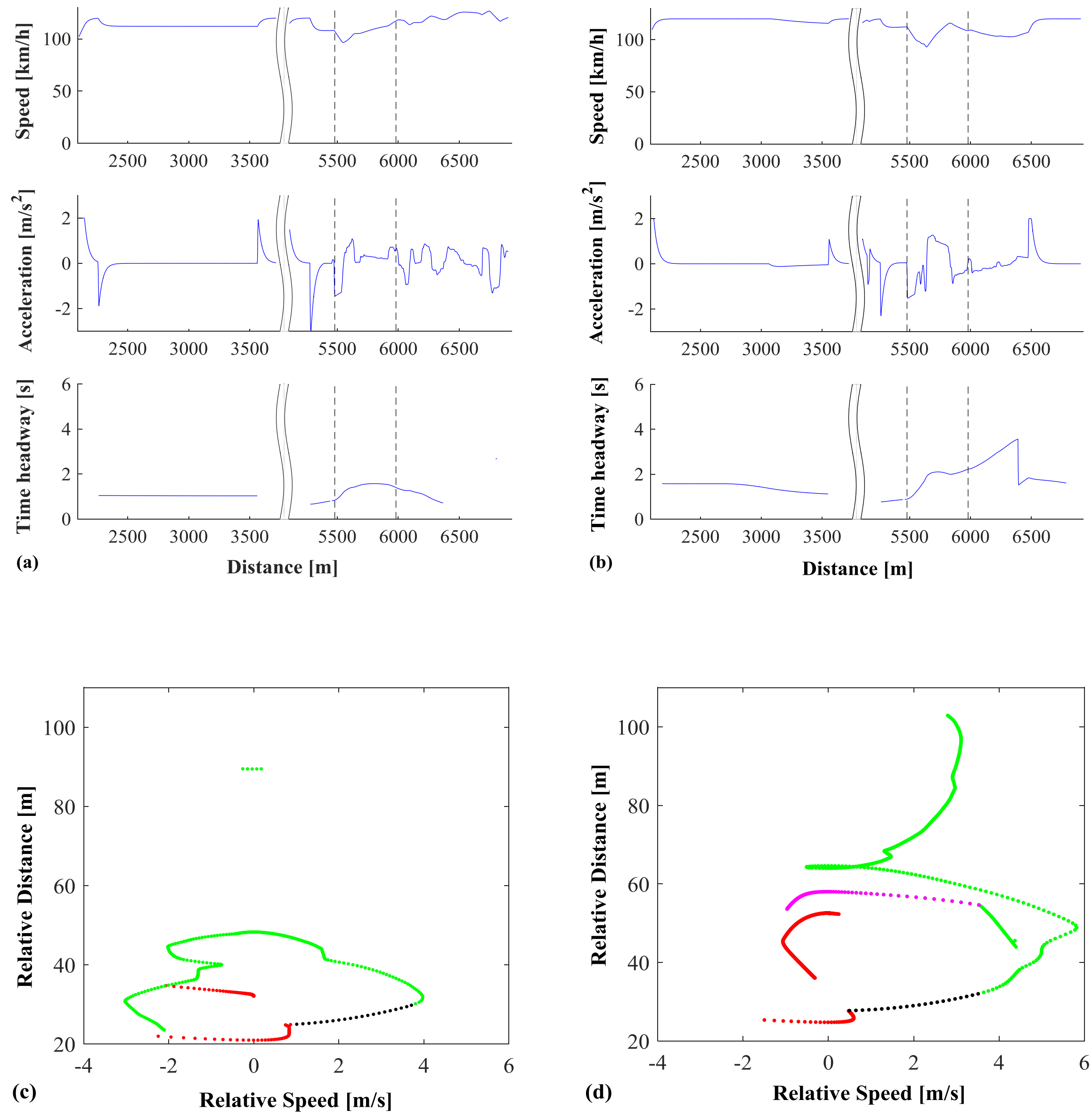


Figure 2.4: Speed, acceleration and time headway distributions calculated as a function of the distance travelled since the beginning of the simulation in the experimental condition 1 (EC1) for (a) Driver 1 and (b) Driver 2. The *(dv, s)* planes in EC1 are reported for (c) Driver 1 and (d) Driver 2. Four phases are distinguished: ACC before sensor failure (red), AIDC control transition (black), manual driving after resuming control (green), ACC after DIAC control transition (magenta). Each dot corresponds to a time step.

Note: The curve lines separate the first and the second segment of the freeway. For each segment, drivers entered and exited the freeway through on and off-ramps. The first dashed black line (distance=5480 m) indicates the location where sensor failure is simulated. After sensor failure, drivers were expected to resume manual control. The second dashed black line (distance=5981 m) indicates the location after which it was possible to switch ACC on again.

2.5 Conclusion and future research

The available literature indicates that drivers may prefer to disengage ACC and resume manual control in dense traffic conditions and to perform manoeuvres such as lane changing. Control transitions can have significant effects on the driver behaviour characteristics. However, these studies rely on data collected in FOTs and thus little insight is available on the relationships between the driver and automation initiated control transitions, driver behaviour characteristics and behavioural adaptations of drivers.

This paper has provided an in-depth insight into the influence of these transitions between ACC and manual driving on the longitudinal driver behaviour characteristics (speed, acceleration, time headway). For this purpose, a driving simulator experiment was setup. Participants were asked to drive a vehicle equipped with ACC on a virtual two-lane freeway. In a baseline condition (BC), participants drove manually. In the first experimental condition (EC1), a sensor failure was simulated and the vehicle decelerated at a specific location where drivers were expected to resume manual control. In the second experimental condition (EC2), drivers switched the system off and on voluntarily.

These three conditions were found to differ significantly with respect to their distributions of speed, acceleration and time headway. The BC and the EC2 show speed distributions that seem to be similar in terms of mean and standard deviation. In the EC1, higher mean speeds and lower standard deviation are observable in the first segment of the freeway where ACC was switched on and control transitions were not possible. After the sensor failure, the speed significantly dropped (ΔV=-18.18 km/h) and the standard deviation of speed increased, following from the different responses of drivers. The median time to resume control after sensor failure was equal to 3.85 s. Notably, a similar speed drop is recognizable when the system could be voluntary switched on again (ΔV=-4.22 km/h). The median time before voluntary switching ACC on after the message was equal to 5.80 s. Small mean time headways (1.30 s) were observed in the first segment of the freeway where ACC was activated permanently, while higher mean values (2.10 s) were found in the second segment where the sensor failure was simulated and control transitions were possible.

These results suggest that control transitions between ACC and manual driving may significantly influence the longitudinal driver behaviour characteristics of ACC vehicles. These outcomes seem to be consistent with previous studies in which data from FOT were analysed (Klunder et al., 2009; Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008; Viti et al., 2008). Therefore, the assumed relative validity of driving simulator experiments (Yan et al., 2008) seems to be confirmed. Microscopic traffic flow models that capture the empirical findings in this study are needed to assess accurately the impacts of control transitions between ACC and manual driving on traffic flow efficiency and safety. Implementing these advanced models into a microscopic traffic flow simulation, the impact of control transitions on capacity, capacity drop and string stability can be investigated more realistically than in current traffic flow simulations. The speed drop after the system failure can, for instance, result in string instability at high penetration rates of ACC vehicles. The key implication of this study is that control transitions should be accounted for when investigating the effects of ACC on traffic flow.

The driving simulator appears to be a useful instrument to do an in-depth investigation of the effects of control transitions on longitudinal driver behaviour characteristics with a high level of controllability. However, further analysis is necessary to better understand the role of driver initiated control transitions and to validate the results obtained in the driving simulator experiment by using data from FOTs. Notably, these findings are dependent on the characteristics of the ACC system designed and cannot be directly generalised to other systems. A limitation of this study is that participants drove for a very short period of time and because of this, little insight is gained on the variations within drivers. In addition, these results are related to light traffic flow condition and cannot be directly extended to dense traffic flow. Further research directions might be as follows. First, driving behaviour could be analysed in terms of lateral driver behaviour characteristics. Second, more work is needed in order to assess the performances of current mathematical models during control transitions. Third, new mathematical models accounting for these transitions could be developed and implemented into a microscopic simulation to investigate the effects on traffic flow. Fourth, the research could be extended to investigate control transitions in case of partial and high automation.

Chapter 3

Driver behaviour characteristics during control transitions from full-range Adaptive Cruise Control to manual driving: an on-road experiment

Results in Chapter 2 showed that the speed dropped after a sensor failure with ACC (AIDC transition). Further analysis was needed to investigate the driver behaviour characteristics when drivers resume manual control voluntarily (DIDC transitions). FOTs have showed that the mean driver behaviour characteristics (values aggregated over 10-s intervals) change significantly after ACC systems that are inactive at low speeds are deactivated. However, these studies do not analyse explicitly variations in medium-dense traffic flow conditions, disregard any temporal evolution over the 10-s intervals, and do not control for the confounding effect of any additional control transitions initiated within these time intervals. Therefore, the influence of DIDC transitions on the driver behaviour characteristics is still unclear.

This chapter quantifies potential adaptations in speed, acceleration, distance headway and relative speed after the ACC is deactivated or overruled by pressing the gas pedal (DIDC transitions), based on a dataset collected in an on-road experiment. The chapter is structured as follows. Section 3.1 introduces driver behaviour during control transitions. Section 3.2 reviews advantages and disadvantages of on-road data collection methods, adaptation effects in longitudinal driver behaviour when manual control is resumed, and limitations of data analysis methods for repeated measures. Section 3.3 describes the specifications of the ACC system, the experimental design, and the data collection on a 35.5 km freeway in Munich during peak hours. This dataset was used in Chapters 4-5 to analyse the main factors that influence drivers' choice to transfer control. Section 3.4 describes the dataset and Section 3.5 the exploratory data analysis. The linear mixed-effects models capturing adaptations in driver behaviour characteristics over time are described in Section 3.6. The estimation results are presented in Section 3.7. Section 3.8 discusses the relevance of the insights for the development of new driving assistance systems and driver behaviour models. Section 3.9 summarizes the main findings and directions for future research.

This chapter is an edited version of the following paper:

Varotto, S.F., Farah, H., Bogenberger, K., Van Arem, B., Hoogendoorn, S.P., Under review. Adaptations in driver behaviour characteristics during control transitions from full-range Adaptive Cruise Control to manual driving: an on-road study. *Transportmetrica A: Transport Science.*

NOTE: The original paper was subject to minor textual revision.

3.1 Introduction

Automated vehicles and systems supporting drivers in their control task can contribute to a reduction of traffic congestion and accidents. Automated vehicles may improve traffic flow stability, accelerate the outflow from a queue, and increase road capacity (Hoogendoorn et al., 2014). Automated vehicles are also expected to mitigate traffic accidents by reducing driver error, which is responsible for the majority of collisions (International Transport Forum, 2015). To predict these impacts, it is essential to understand how the driving assistance systems that are currently available influence the performance of the driving task. The influence of Adaptive Cruise Control (ACC) systems on driver behaviour has been an object of research, mainly in driving simulator experiments, since the 1990s. The ACC has a direct adaptation effect on the longitudinal control task of drivers because it keeps a target speed and time headway (Martens and Jenssen, 2012). On-road experiments (Alkim et al., 2007; Malta et al., 2012; NHTSA, 2005; Schakel et al., 2017) have shown that ACC systems have a substantial impact on driver behaviour. When the ACC system is used, drivers maintain larger time headways (Alkim et al., 2007; Malta et al., 2012; NHTSA, 2005; Schakel et al., 2017), spend more time in the middle and left lane (fast lane) and change lanes beforehand to avoid possible interactions with slower vehicles (Alkim et al., 2007). However, these results might be determined by the traffic situations in which the ACC system is activated (e.g., non-critical traffic situations, light-medium traffic conditions, and medium-high speeds).

In certain situations, drivers might choose to disengage the ACC system and resume manual control, or the system disengages because of its operational limitations. These transitions between automation and manual driving are called *control transitions* (Lu et al., 2016) and may influence considerably traffic flow efficiency (Varotto et al., 2015) and safety (Vlakveld et al., 2015). Lu et al. (2016) categorized control transitions based on who (driver or automation) initiates the transition and who is in control afterwards. In this framework, transitions are defined as 'Driver Initiates transition, and Driver in Control after' (DIDC) when drivers deactivate the system, 'Driver Initiates transition, and Automation in Control after' (DIAC) when drivers activate it, and 'Automation Initiates transition, and Driver in Control after' (AIDC) when the system deactivates because of its operational limitations. The situations in which these transitions happen are related to the functioning of the driver assistance system, the road, the traffic flow, and the drivers themselves (Varotto et al., 2014). Field Operational Tests (FOTs) have suggested that drivers initiate DIDC transitions with ACC systems that are not operational at low speeds to avoid potentially safety-critical traffic situations (Xiong and Boyle, 2012) and to regulate the speed before changing lane (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008) (for a detailed review, see Varotto et al. (2017)). When drivers deactivate the system, the mean time headway and the mean acceleration decrease significantly (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008). These significant changes in the mean driver behaviour characteristics can be interpreted as adaptation effects on the driver control task. Further analysis is needed to analyse the duration of these adaptations. Recently, *full-range* ACC systems that operate at low speeds in stop-and-go conditions have been introduced into the market. These systems might be activated and deactivated in different circumstances and result in different adaptation effects. Recently, controlled on-road studies have shown that full-range ACC systems are deactivated when the subject vehicle approaches a slower leader (Varotto et al., 2017), changes lane (Pereira et al., 2015), and exits the freeway (Pereira et al., 2015; Varotto et al., 2017). These systems are overruled by pressing the gas pedal a few seconds after activation and when the vehicle decelerates (Varotto et al., 2017). However, these studies did not analyse possible adaptation effects in the driver behaviour characteristics after the full-range ACC was deactivated or overruled by pressing the gas pedal.

Full-range ACC systems might have a beneficial impact on traffic flow efficiency in dense traffic (Van Driel and Van Arem, 2010). To assess this impact at varying penetration rates, mathematical models of automated and manually driven vehicles can be implemented into microscopic traffic flow simulations. To date, most car-following and lane-changing models used to assess the impact of ACC do not describe control transitions. A few mathematical models (Klunder et al., 2009; Van Arem et al., 1997; Xiao et al., 2017) have implemented deterministic decision rules for transferring control and have ignored possible adaptation effects in manual driving behaviour before the system is activated and after the system is deactivated. Therefore, the effects on traffic flow forecasted by these models could be unrealistic. The behavioural realism of the mathematical models available can be improved by incorporating findings from human factors and driver psychology (Hamdar et al., 2015; Saifuzzaman and Zheng, 2014).

This study analyses speed, acceleration, distance headway and relative speed during control transitions from full-range ACC to manual driving using statistical analysis methods. These driver behaviour characteristics were chosen because they are relevant to represent the longitudinal control task of drivers in microscopic traffic flow models. The aim of this statistical analysis is to identify possible adaptation effects in longitudinal driver behaviour in the first few seconds after the system has been deactivated and after it has been overruled by pressing the gas pedal. To this purpose, a controlled on-road experiment was designed and driver behaviour data were collected on the A99 freeway in Munich during peak hours.

3.2 Literature review

Section 3.2.1 provides an overview on on-road data collection methods. Section 3.2.2 describes adaptations in driver behaviour characteristics during control transitions from ACC to manual driving based on on-road studies in real traffic. In this study, adaptions are defined as the significant changes in the driver behaviour characteristics in the first few seconds after the ACC system has been deactivated. Notably, control transitions have also been analysed in driving simulator experiments which have mainly focused on reaction times in automation failures (for a review, see Varotto et al. (2015)). Section 3.2.3 proposes statistical analysis methods that are suitable to analyse adaptations in driver behaviour characteristics. Section 3.2.4 concludes the literature review by defining the research gaps and formulating the research hypotheses that are tested in this study.

3.2.1 On-road data collection methods

On-road studies provide researchers with a unique possibility of analysing driving behaviour in real traffic. These studies may be classified into three groups (for a comprehensive review, see Carsten et al. (2013)): controlled on-road studies, Field Operational Tests, and naturalistic driving studies. Controlled on-road studies consist of limited experiments designed to answer specific research questions (Carsten et al., 2013). The defining characteristic of these studies is using a pre-set route to investigate changes in driving behaviour under different conditions. FOTs and naturalistic studies are large-scale and long-term experiments focusing respectively on the evaluation of a certain treatment (e.g., a new driving assistance system or a training program) and the diagnosis of regular driving behaviour (e.g., investigating the causes of pre-crash events) (Carsten et al., 2013). Participants usually drive a new vehicle equipped with the system that should be tested in controlled experiments and FOTs, and their own vehicle in naturalistic studies. The main advantages of controlled on-road studies compared to the other two are the following: possibility of controlling for confounding factors (e.g., road design, traffic flow conditions, time of the day and weather), increasing the exposure to the conditions under investigation (e.g., congestion), and accommodating an observer in the test vehicle. The main disadvantage of this method is a possible reduction in external validity due to the controlled nature of the experiment (e.g., the presence of the observer might influence drivers' behaviour).

3.2.2 Adaptations in driver behaviour characteristics during transitions to manual control

Control transitions can be initiated by the automated system because of its operational limitations or by the driver voluntarily. Several FOTs (Alkim et al., 2007; NHTSA, 2005; Viti et al., 2008; Xiong and Boyle, 2012) have analysed driver behaviour with ACC systems that are not operational at speeds below 30 km/h (or 20 mph) and have limited decelerations capabilities. A few studies (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008) have analysed changes in the means and standard deviations of the driver behaviour characteristics before and after the control transitions (values aggregated over 10-s intervals) using a repeated measures analysis of variance (ANOVA). After the ACC system was deactivated (DIDC transitions to Inactive), the mean time headway decreased significantly (from 1.79 to 1.40 s), the standard deviation of speed decreased (from 15.5 to 11.4 km/h), the mean acceleration decreased (from -0.02 to -0.40 m/s^2) and the standard deviation of acceleration increased (from 0.22 to 0.35 m/s^2). These results suggest that drivers braked and drove closer to the leader after deactivating the system. After the ACC was overruled by pressing the gas pedal (DIDC transition to Active and Accelerate), the mean acceleration increased significantly (from –0.03 to 0.10 m/s^2). This finding suggests that drivers pressed the gas pedal for a few seconds after overruling the system. Recently, controlled on-road studies have analysed the situations in which drivers resume manual control in *full-range* ACC (Pereira et al., 2015; Varotto et al., 2017). However, these studies did not analyse potential adaptation effects in the driver behaviour characteristics after the system was deactivated or overruled by pressing the gas pedal.

In summary, previous studies (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008) have gained limited insight on the duration of adaptation effects during control transitions because the 10-s intervals were chosen arbitrarily and any temporal evolution of the driver behaviour characteristics over these time intervals was ignored. Since traffic density levels were not captured explicitly, it is not clear whether adaptations in the mean driver behaviour characteristics occur in medium-dense traffic flow conditions, which are more relevant to understand impacts on traffic efficiency and safety. In addition, these studies did not control for the confounding effect of any additional control transitions initiated within these time intervals, when the system was deactivated or overruled by pressing the gas pedal for less than 10 s. A more in-depth analysis is needed to control for these factors.

The time needed by drivers to stabilize their behaviour after AIDC transitions was analysed by Merat et al. (2014) in a driver simulator experiment with a high degree of controllability. Driver behaviour measurements over consecutive 5-s time intervals were compared using repeated measures ANOVA. A similar approach can be used to investigate adaptations in driver behaviour characteristics after DIDC transitions. However, repeated measures ANOVA is only suitable to analyse data in which the hierarchical structure is simple (e.g., subjects and repetitions over time for each subject), the same number of repetitions are available for each subject, and all observations are complete. To analyse the impact of several observable and unobservable factors simultaneously on the driver behaviour characteristics in an experiment with a higher degree of validity, a flexible data analysis technique is needed which captures variations between subjects and correlations between observations over time for the same subject.

3.2.3 Statistical analysis methods for adaptations in driver behaviour

Few studies have analysed adaptations in driver behaviour capturing the impact of several explanatory factors and interdependencies between repeated observations over time for the same subject. For this purpose, recent studies have proposed linear mixed-effects models for repeated measures, which can accommodate both fixed and random effects capturing complex error structures (Albert, 2017; Geden et al., 2017; Oviedo-Trespalacios et al., 2017; Peng and Boyle, 2015; Peng et al., 2014; Saad et al., 2018; Wang et al., 2017). Linear mixed-effects models allow to define explicitly a hierarchical structure (e.g., subjects and occasions within subjects) and a residual variance-covariance structure (e.g., correlations between consecutive observations over time) (Pinheiro and Bates, 2000; Tabachnick and Fidell, 2013). Alternative model structures and residual variance-covariance structures can be tested and compared based on statistical significance (Verbeke and Molenberghs, 2009; Zuur et al., 2009). Notably, linear mixed-effects models are robust against unequal number of repetitions for each subject and missing data which are frequent in on-road experiments. The model can be used to predict the estimated marginal means of the dependent variable in different treatment levels for each factor. Pairwise comparisons can be used to test statistically differences between specific treatment levels, controlling for the confounding effect of the fixed and random effects which are captured in the model (Quené and van den Bergh, 2004). This overview concludes that linear mixed-effects models are a suitable data analysis technique to capture adaptations in driver behaviour characteristics over time.

3.2.4 Research gaps and hypotheses

In summary, FOTs have shown significant changes in the mean driver behaviour characteristics before and after control transitions with ACC systems that are not operational at low speeds (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008). These studies compared the mean values of the driver behaviour characteristics aggregated over 10-s intervals in a wide range of traffic situations using repeated measures ANOVA (before vs. after control transitions). However, limited insight was gained on the duration of these adaptation effects, on the magnitude of these adaptations in medium-dense traffic flow conditions, and on the confounding effect of any additional control transitions initiated within these time intervals. Repeated measures ANOVA is not suitable to analyse data collected in experiments with a high degree of validity, in which the hierarchical structure is complex (e.g., subjects, occasions within subjects, repetitions over time within occasions), a different number of repetitions is available for each subject, and some observations are missing. To capture the impact of several observable and unobservable factors simultaneously on the driver behaviour characteristics in these experiments, a flexible data analysis technique is needed. Quantifying the *duration* and *magnitude* of significant adaptations in driver behaviour characteristics after drivers resume manual control represents the first step towards understanding driver interaction with the system. In particular, analysing driver behaviour characteristics in dense traffic is more relevant to develop mathematical models that describe driver behaviour in these conditions and are suitable to assess potential impacts of control transitions on traffic flow efficiency. It should be clarified that the statistical analysis proposed in this study provides an empirical foundation for developing microscopic traffic flow models but does not aim directly at developing mathematical models that can be implemented into a microscopic traffic flow simulation. In this paper, the following two main research hypotheses are tested based on driver behaviour data collected in an on-road experiment:

H_1: The mean speed, acceleration, distance headway, and relative speed change significantly over a certain time period (*transition period*) when drivers resume manual control after the ACC system is deactivated or overruled;

H_2: The duration of this transition period and the magnitude of the adaptation in driver behaviour characteristics vary significantly depending on the traffic density.

The data analysis is structured as follows. Section 3.6 presents descriptive statistics to explore the relationships existing between driver behaviour characteristics in control transitions and ACC system states, average traffic density conditions, and time period after transferring control. Section 3.7 proposes linear mixed-effects models to analyse the temporal evolution of the mean driver behaviour characteristics in different traffic conditions accounting for the ACC system states. Pairwise comparisons of the estimated marginal means are used to test statistically the research hypotheses H_1 and H_2. In Section 3.8, the results reveal the duration and magnitude of the transition periods for each type of control transition.

3.3 Experimental set-up

Section 3.3.1 describes the characteristics of the full-range ACC system and Section 3.3.2 presents the data collection systems used in the on-road experiment. Section 3.3.3 describes the test route on the A99 freeway in Munich, Section 3.3.4 details the experimental design, and Section 3.3.5 presents the participants and the data collection.

3.3.1 ACC system specifications

The research vehicle (BMW 5 series, 2013) was equipped with a regular version of full-range Adaptive Cruise Control (ACC) and a Lane Change Warning (LCW). The ACC system takes over speed control at speeds between 0 and 210 km/h and adapts the following distance to the vehicle in front at speeds higher than 30 km/h. The target time headways that can be set are 1.0, 1.4, 1.8, and 2.2 s. The maximum acceleration and deceleration supported by the system are 3 m/s^2 and –3 m/s^2. The radar range is equal to 120 m. When the radar does not detect any vehicle in front in the same lane (leader), the system functions as a cruise control and keeps the speed set by the user (free speed). When the vehicle stands still for less than 3 s, the system restarts the engine automatically and the vehicle moves off. However, the system is not able to regulate the speed and following headway based on objects that stand still. The LCW system detects vehicles that approach at high speeds in the adjacent lanes and warns the driver by a light on the wing mirrors. In addition, drivers are warned by a vibration of the steering wheel and a flashing light when they set the turning indicator to change lane in a safety critical situation. The LCW system is not active at speeds below 70 km/h. This study focuses on the functioning of the full-range ACC only.

The ACC system can be in each single moment in one of the following states: *Off* (O), *Inactive* (I), *Active* (A), *Active and Accelerate* (AAc). Figure 3.1 presents possible DIDC and DIAC transitions. Pressing the on/off button once, drivers can transfer from O to I, and, pressing it a second time, from I to A. Control transitions between O and I were executed when the system was activated for the first time at the beginning of the test trial and will not be analysed in the remainder of this thesis. The system can also be activated (to A) using the switch to regulate the desired speed or the resume button, which re-engages the desired speed and time headway previously used (Resume ACC). When the system is active, it is possible to set a target speed and time headway by using the switches. The system transfers to AAc when the gas pedal is pressed, and back to A, maintaining the settings previously stored, when the gas pedal is released. The system can be disengaged (to I) by braking or by pressing the on/off button. However, the system cannot handle all possible driving situations (e.g., safety critical situations) and might fail unexpectedly without any warnings (AIDC). The system switches off automatically (to I) when the vehicle stands still for more than 3 seconds (e.g., in congestion), when the system-support constraints (e.g., maximum deceleration) are reached in a safety critical situation and as a result a Take Over Request (TOR) is triggered, and in case of a system failure (e.g., the sensors cannot work properly and the system is switched off without warning the driver). After ACC switches off automatically at speeds equal to zero, the system is re-engaged when the driver presses the gas pedal (I to AAc).

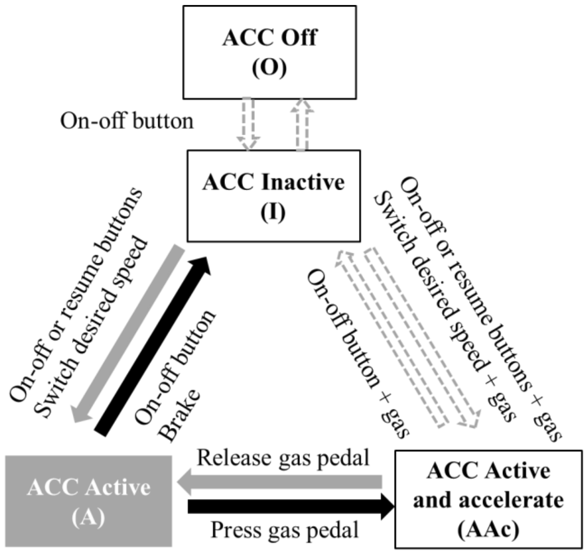


Figure 3.1: Control and state transitions between ACC system states that can be initiated by drivers.

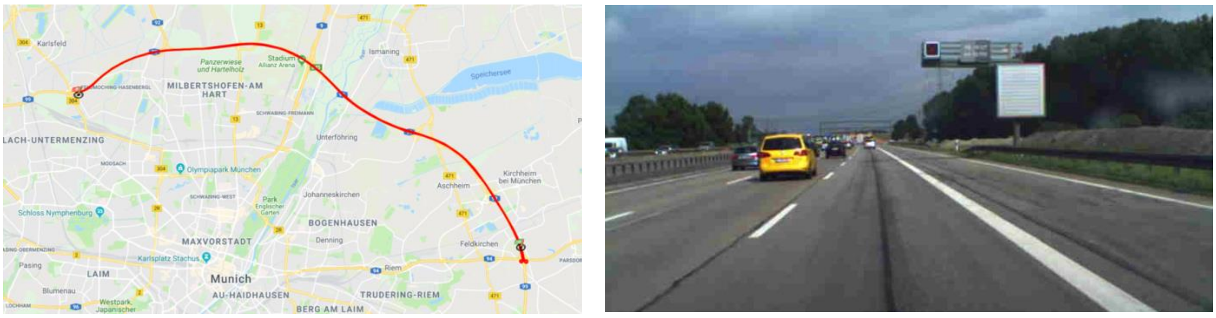
Note: White boxes denote system states in which drivers are in control, while grey boxes states in which ACC is in control. Solid arrows indicate control transitions, while dashed arrows state transitions. Grey solid arrows define DIAC transitions, black solid arrows DIDC transitions.

3.3.2 Data collection systems (sensors)

GPS position, ACC system state and settings, speed, acceleration, distance headway (from radar), and speed of the leader (from radar) were measured and registered in the Controller Area Network (CAN) of the instrumented vehicle. The data were recorded at a frequency of 1 Hz (GPS position), 15 Hz (e.g., distance headway), and 50 Hz (e.g., speed of the subject vehicle). In addition, lane-specific mean speeds and counts were recorded by dual inductive loop detectors at one minute intervals.

3.3.3 Test route

The test route was pre-set in the navigation system to allow a valid comparison between participants. It comprised four freeway segments (Figure 3.2 *a*) mostly composed of three lanes per direction (Figure 3.2 *b*) on the A99 in Munich (46 km in total). Drivers entered and exited each freeway segment. This route was selected based on traffic data which showed high density conditions during peak hours. The outward journey to reach the entrance of the freeway, on-ramps, connections, off-ramps and the return journey after exiting were not included in the analysis.



(a) **(b)**

Figure 3.2: (a) Map of the test route on the A99 in Munich (Google Maps, viewed 17 May 2018) and (b) picture of the basic freeway section.

3.3.4 Experimental design

The experiment consisted of a single drive along a pre-set test road (*controlled on-road study*) that comprised different traffic flow conditions (i.e., light, medium and dense traffic) and freeway sections, resulting in a *within-subjects experimental design*. In the first freeway segment, participants tested the system and found their preferred time headway setting. During the experiment on the remaining three freeway segments, participants were instructed to drive as they normally would do in real-life and use the ACC system only when they thought it was appropriate. Therefore, they could overrule the system and regulate the desired speed at any time. LCW was active all the time and could not be deactivated.

3.3.5 Participants and data collection

A sample of twenty-three participants with a valid driving license and more than one year of driving experience was recruited from the BMW employees in Munich. All of them completed the experiment successfully. Fifteen participants were males, and eight were females. Participants were aged between 25 and 51 years old (M = 31.57, SD = 6.73). Six participants had no experience with Advanced Driving Assistance Systems (ADAS), nine were used to drive with ADAS less than once a month and eight more often than once a month. None of them had been directly involved in the development of the system. The experiment was conducted from June, 29th to July, 9th 2015 during the morning (7-9 am) and the evening (4-6 pm, 6-8 pm) peak hours. Participants received written instructions on the potential safety risks, the specifications of the systems, and the general scope of the research before the experiment. However, the precise purpose of the experiment (i.e., analysing driving behaviour during control transitions) was not communicated. Participants signed a written informed consent form according to the ethical regulations of Delft University of Technology. The duration of test drive was between 45 and 90 minutes based on the traffic flow conditions.

3.4 Datasets used

Section 3.4.1 discusses the CAN-bus data and Section 3.4.2 the loop detector data that were collected during the experiment and analysed in this study.

3.4.1 CAN-bus data

Only the data registered on the three freeway segments being part of the experiment were processed. In the dataset (23 drives of 35.5 km each) there were 378 transitions to manual control, 326 of which were initiated by drivers and 52 were initiated by the ACC system. Table 3.1 reports the occurrences of each type of transition. Drivers transferred most frequently from A to AAc (54.8% of total) and deactivated the system most often by using the brake pedal. Analysing the transitions initiated by the ACC system shows that the ACC switched off most often in a stand-still and sometimes because of an unexpected failure. Notably, the occurrences of these failures are not representative of the system functioning in a serial car. Two TORs happened in safety critical situations (cut-in manoeuvres) when the maximum deceleration of the system was not sufficient to avoid collision and the driver had to brake manually. This study will analyse only the transitions initiated by drivers.

Table 3.1: Number and percentage of transitions to Inactive (A to I) and to Active and accelerate (A to AAc) based on initiation mode

Transition type	Transition initiation			
	Driver		ACC	
A to I	119 (31.5% of total)		52 (13.8% of total)	
	Initiation mode:		Initiation mode:	
	On/off button	19 (16.0%)	Stand still	42 (80.8%)
	Brake	100 (84.0%)	System failure	8 (15.4%)
			Take Over Request	2 (3.8%)
A to AAc	207 (54.8% of total)		-	
	Initiation mode:			
	Press gas pedal	207 (100%)		

3.4.2 Loop detector data

The test road is equipped with 30 stationary detectors which provide lane-specific time mean speeds and counts at one minute intervals. The detectors are placed at a distance between 320 m and 2250 m (M=1273 m, SD=441 m) as presented in the road network in Figure 3.3 *a* and Figure 3.3 *c*. Two detectors did not record any data, all detectors malfunctioned for 24 hours and some of them malfunctioned temporarily during the experiment due to failures in the communication system. The valid loop detector data recorded during the experiment were processed using the Adaptive Smoothing Method (ASM) to reconstruct the general traffic conditions as smooth functions of space and time (Treiber and Helbing, 2002). The ASM is preferred to simple interpolation because it accounts for the characteristic propagation velocities in free and congested traffic, and it is suitable to reconstruct traffic when some detectors fail and the distance between valid detector measurements is shorter than 3 km (Treiber and Helbing, 2002). As a result, the mean speed, traffic flow and density were calculated for each lane at a space resolution of 100 m and time resolution of 30 s.

CAN-bus data and loop detector data were synchronized (manually). Figure 3.3 *b, c* presents the trajectory of a participant on a time-space speed contour plot of the lane in which the vehicle was in during the experiment. The driver maintained the ACC system active most of the time in a full-speed range and transferred control more often in dense traffic conditions. At the beginning of the first segment being part of the experiment (Figure 3.3 *d*), the driver transferred from A to AAc and from A to I multiple times before changing lane in dense traffic conditions. In medium and light traffic conditions, control transitions were initiated less frequently (e.g., A to I before exiting the freeway in Figure 3.3 *d*). At the end of the third freeway segment (Figure 3.3 *b*), the ACC system deactivated automatically after the vehicle stood still for more than 3 seconds in very dense traffic. However, the driver re-activated the system as soon as the leader moved off. These results support the relevance of the current study showing that, in contrast with previous findings on ACC systems that are not operational at low speeds (Viti et al., 2008), the full-range ACC was used in dense traffic conditions.

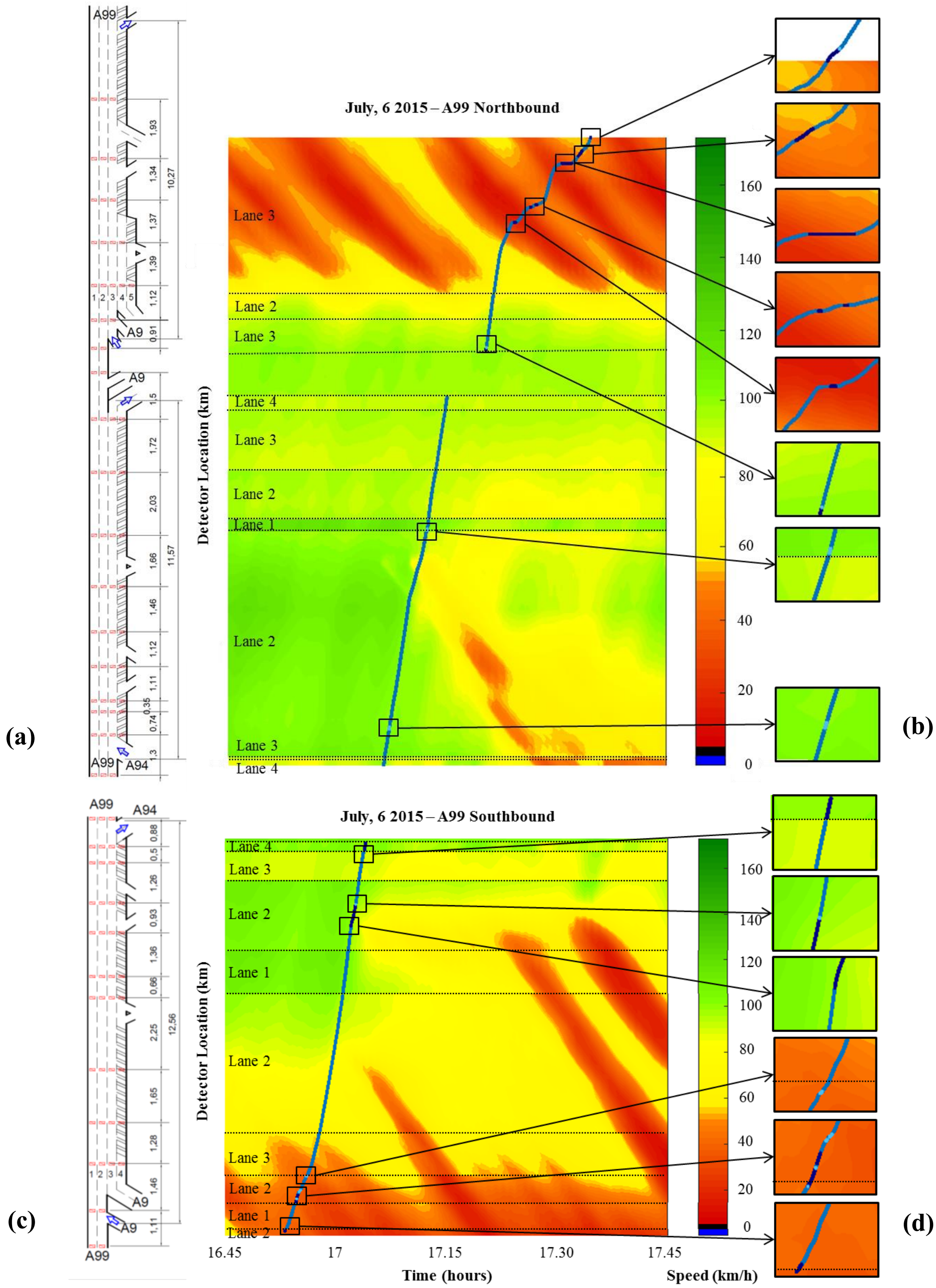


Figure 3.3: Road network of the test site: (a) northbound A99, and (c) southbound A99. (b, d) Trajectory of a test vehicle (blue line) and time-space speed contour plots of the lane in which the vehicle was in during the experiment.

Note: In (a) and (c), red boxes represent the loop detectors, and blue arrows the locations where the vehicle entered and exited each segment. In (b) and (d), dark blue dots represent ACC Inactive, blue ACC Active, and light blue ACC Active and accelerate.

3.5 Data processing

To gain insight into driver behaviour during control transitions, the longitudinal driver behaviour characteristics (speed, acceleration, distance headway, and relative speed) were analysed in the intervals 10 s before and 10 s after each transition. These driver behaviour characteristics were selected because they are relevant to develop a microscopic traffic flow model. The time intervals were chosen because they are considered suitable to execute a manoeuvre (e.g., the average lane change duration is equal to 5-6 s (Toledo and Zohar, 2007)) and were used in a similar previous study (Pauwelussen and Feenstra, 2010). The measurements were reduced to a 1 Hz frequency to test significant changes in the mean variables over time (within the 10-s intervals) and interaction effects with the system states (H_1) and the traffic density levels (H_2).

Average density levels were calculated by using the lane-specific loop detector measurements. Unreliable loop detectors measurements (mean speeds below 72 km/h at densities lower than 22 veh/km/lane, and mean speeds below 36 km/h) were discarded as suggested by Knoop and Daamen (2014). To compare changes in driver behaviour characteristics in different traffic conditions, the observed transitions were classified into three density levels as follows:

- *low density,* if the detector measurements were considered reliable and the mean density was lower than 11 veh/km/lane (i.e., HCM level of service A and B (Transportation Research Board, 2010)), or if the loop detector measurements were discarded and the mean speed of the leader over the 20-s interval was higher than 110 km/h, or if the loop detector measurements were discarded and the leader was not detected by the radar over the 20-s interval (i.e., distance headway larger than 120 m);
- *medium density*, if the detector measurements were considered reliable and the mean density was between 11 and 22 veh/km/lane (i.e., HCM level of service C and D (Transportation Research Board, 2010)), or if the detector measurements were considered unreliable and the mean speed of the leader was between 80 and 110 km/h;
- *high density*, if the detector measurements were considered reliable and the mean density was higher than 22 veh/km/lane (i.e., HCM level of service E and F (Transportation Research Board, 2010)), or if the detector measurement was discarded and the mean speed of the leader was lower than 80 km/h.

3.6 Data analysis

This paper analyses 119 DIDC transitions to I (36 at low densities, 50 at medium densities, and 33 at high densities) and 207 DIDC transitions to AAc (63 at low densities, 96 at medium densities, and 48 at high densities). Transitions to I comprise 2380 1-s observations for speed and acceleration and 2003 1-s observations for distance headway (front bumper to rear bumper) and relative speed (speed of the leader minus speed of the subject vehicle), while transitions to AAc 4140 1-s observations for speed and acceleration and 3544 1-s observations for distance headway and relative speed. Distance headways and relative speeds are considered missing if the radar does not detect any leader (i.e., sudden leader change due to a cut-in or a lane change, and distance headway larger than 120 m). Drivers differed considerably in the number of transitions executed. During the 35.5-km test drive, drivers transferred to I from 1 to 13 times (M=5.17, SD=2.72) and to AAc from 0 to 43 times

(M=9.00, SD=9.52). Some drivers drove with the system active most of the time, others resumed manual control frequently or drove mainly manually. These results suggest that differences between drivers should be accounted for when analysing driver behaviour during control transitions. The remainder of this section explores, at an aggregate level, the relationships existing between driver behaviour characteristics during control transitions and ACC system states, average traffic density conditions, and time period before and after transferring control.

Table 3.2 shows the mean and standard deviation (values aggregated over 10-s intervals) of speed, acceleration, distance headway and relative speed for each density level in the 10-s interval before and 10-s after the transitions. Paired samples t-tests were performed to check whether the differences in these mean values were significant. Figure 3.4 and Figure 3.5 present the means and standard deviations of speed, acceleration, distance headway and relative speed over time in the 10-s interval before and 10-s after the transitions. The percentages of observations in each system state are also represented as a function of time.

Driver behaviour characteristics during control transitions from A to I showed similar changes in the three traffic conditions (Table 3.3): the mean speeds and accelerations decreased significantly, the standard deviation of speeds and accelerations increased significantly, and the mean distance headways decreased significantly. Figure 3.4 *a-c* show that the mean speed, the mean acceleration, and the mean distance headway were almost constant before deactivation and decreased afterwards in each traffic condition. Figure 3.4 *b* shows that the mean acceleration decreased relatively with a sharp drop 0-1 s after the transition and increased for a few seconds afterwards. The standard deviation of relative speed increased significantly at medium densities. Figure 3.4 *d* shows that the mean relative speed decreased before the transition and increased afterwards. These results suggest that drivers deactivated the ACC system when approaching a slower leader. Most drivers braked to deactivate the system and then released the brake pedal after few seconds. Therefore, the speed and the distance headway decreased. Figure 3.4 *e* shows that, in the 10 s before the transition, the system was active most of the time. Some drivers re-activated the system in the interval 3-10 s after the transition and the system was A or AAc in 28.6% of the observations 10 s after the transition.

When the system was transferred from A to AAc, the mean accelerations increased significantly in each traffic conditions, the standard deviations of speeds increased significantly at medium and high densities, and the standard deviations of accelerations increased significantly at medium densities (Table 3.3). Figure 3.5 *a-b* show that the mean speeds and the mean accelerations slightly decreased before the ACC system was overruled by pressing the gas pedal and increased afterwards in each traffic conditions. Figure 3.5 *c* shows that the mean distance headways were almost constant before and after the transition. The mean standard deviations of relative speeds increased significantly at low and high densities. Figure 3.5 *d* shows that the mean relative speeds increased before the transition and decreased afterwards. Figure 3.5 *e* shows that the system was I or AAc in 28.5% of the observations 10 s before the transition and it transferred to A in the interval 0-6 s before the transition. After the transition, the system was transferred again to A or I, and, 10 s after the transition, it was still AAc in only 42.5% of the observations. Further analysis is necessary to control for the confounding effects of additional control transitions initiated in these time intervals.

These empirical analyses have shown that the means and standard deviations of driver behaviour characteristics change significantly over time in control transitions. The mean profiles differ between traffic flow conditions. In addition, the ACC system is overruled for a few seconds only when the gas pedal is pressed, and certain drivers are more likely to transfer control than others. In the next section, adaptation effects in driver behaviour characteristics will be examined during control transitions using linear mixed-effects models, which control for the effect of all these factors simultaneously (time period, density level, ACC system state, and between-subjects variability).

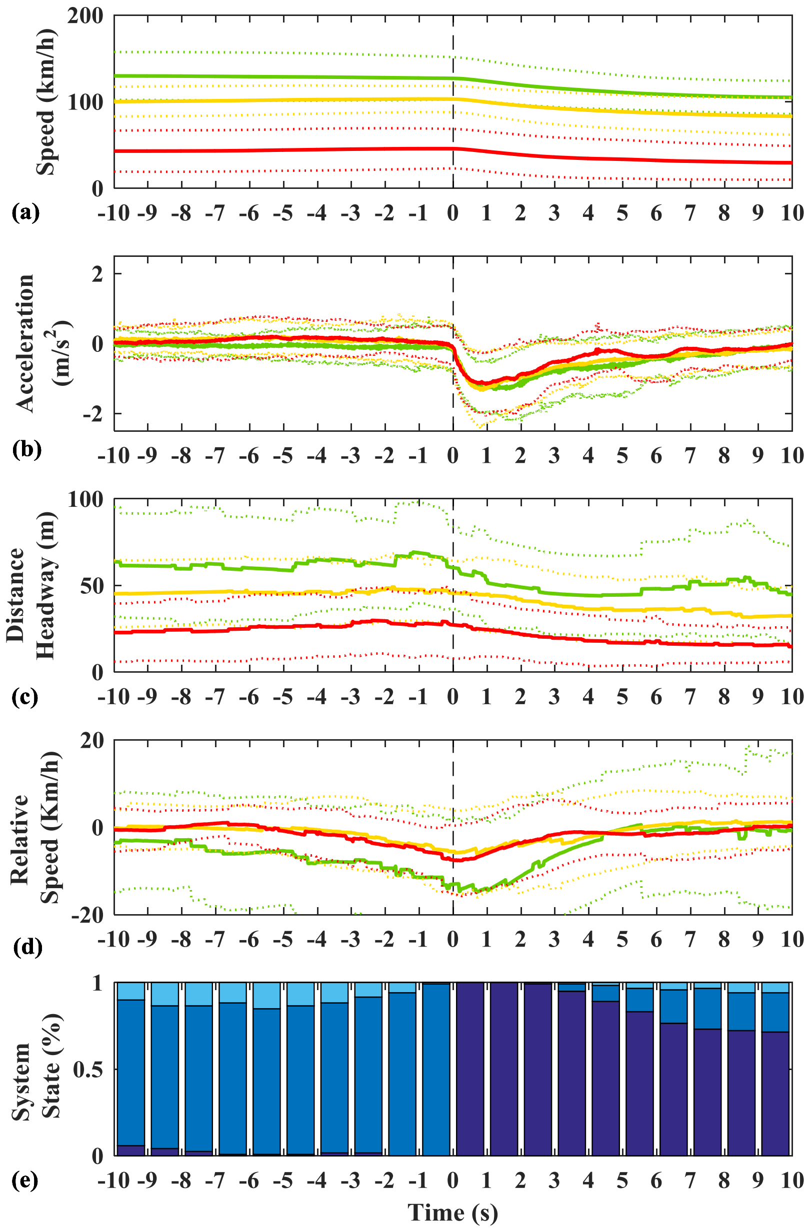


Figure 3.4: Transitions to Inactive (A to I): mean (solid line) and standard deviation (dashed line) of (a) speed, (b) acceleration, (c) distance headway and (d) relative speed calculated as a function of time in the interval 10 s before (-10, 0) and 10 s after (0, 10) the instant when the transition is initiated (dashed black line); (e) percentage of observations in each system state as a function of time.

Note: In (a)-(d), green lines represent low density conditions (0-11 veh/km/lane), yellow lines medium density conditions (11-22 veh/km/lane), and red lines high density conditions (>22 veh/km/lane). In (e), dark blue bars represent Inactive, blue represent Active, and light blue Active and accelerate.

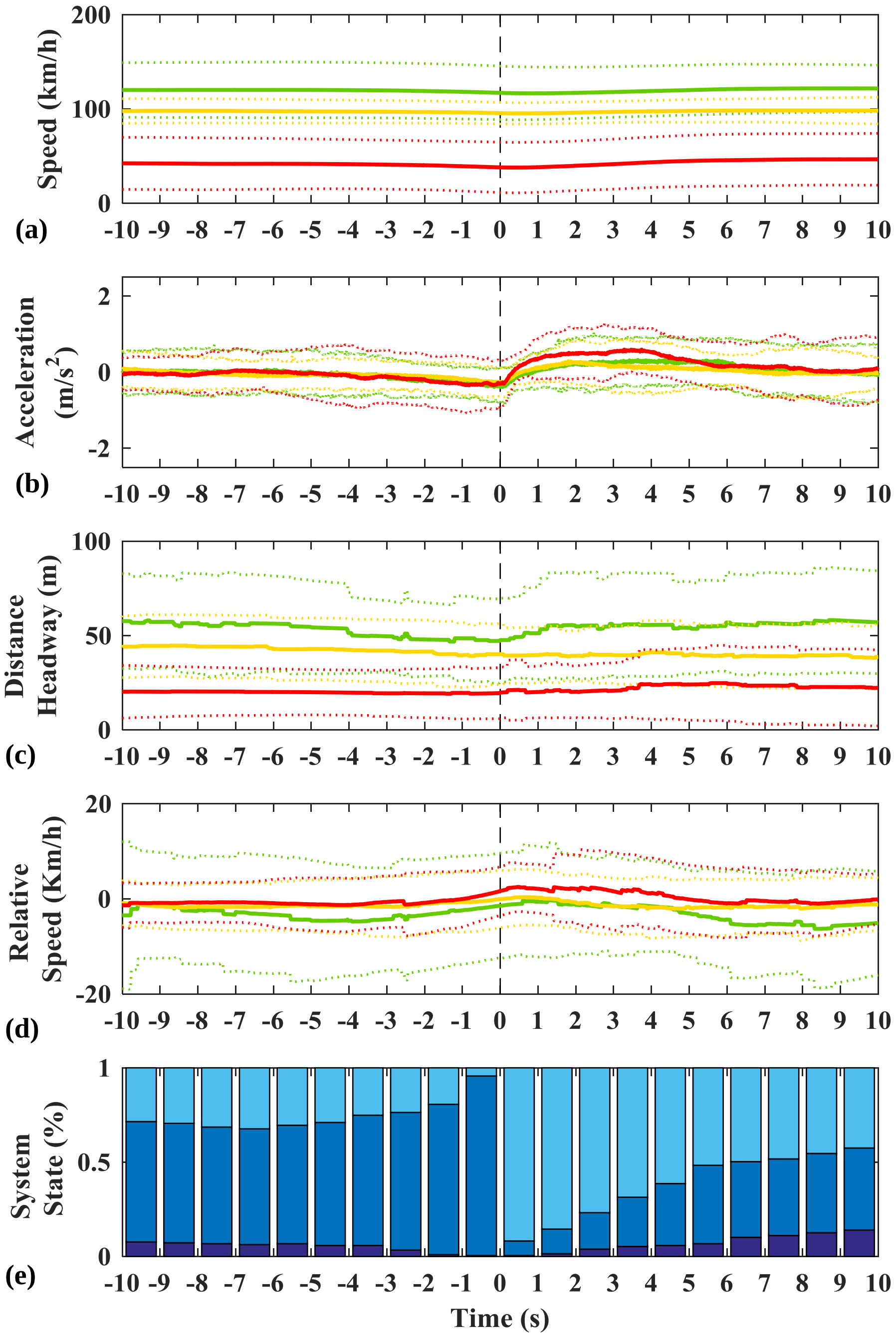


Figure 3.5: Transitions to Active and accelerate (A to AAc): mean (solid line) and standard deviation (dashed line) of (a) speed, (b) acceleration, (c) distance headway and (d) relative speed calculated as a function of time in the interval 10 s before (-10, 0) and 10 s after (0, 10) the instant when the transition is initiated (dashed black line); (j) percentage of observations in each system state as a function of time.

Note: In (a)-(d), green lines represent low density conditions (0-11 veh/km/lane), yellow lines medium density conditions (11-22 veh/km/lane), and red lines high density conditions (>22 veh/km/lane). In (e), dark blue bars represent Inactive, blue represent Active, and light blue Active and accelerate.

Table 3.2: System state in the 10-s interval before and 10-s after the transitions to Inactive (A to I) and to Active and accelerate (A to AAc)

	A to I		A to AAc	
System state	Before	After	Before	After
I	1.8%	86.0%	5.1%	7.1%
A	87.7%	11.5%	69.5%	30.7%
AAc	10.4%	2.5%	25.4%	62.2%
Total	100%	100%	100%	100%

Table 3.3: Speed, acceleration, distance headway and relative speed in the 10-s interval before and 10-s interval after for transitions to Inactive (A to I), and to Active and accelerate (A to AAc): statistics and results of paired samples t-tests

		A to I			A to AAc		
Variable	Density Level	Before	After	p-value	Before	After	p-value
Mean of mean speeds	Low	129	113	<0.0005	120	120	0.988
	Medium	102	90.0	<0.0005	97.2	97.3	0.909
	High	44.3	34.7	<0.0005	41.1	43.4	0.156
Mean of standard deviation of speeds	Low	2.63	7.85	<0.0005	3.70	4.67	0.120
	Medium	3.00	6.69	<0.0005	2.48	3.29	0.042
	High	3.66	5.75	0.042	3.87	5.32	0.050
Mean of mean accelerations	Low	-0.0672	-0.606	<0.0005	-0.0853	0.126	0.005
	Medium	0.104	-0.541	<0.0005	-0.0733	0.0627	0.003
	High	0.0962	-0.435	<0.0005	-0.103	0.256	<0.0005
Mean of standard deviation of accelerations	Low	0.266	0.533	<0.0005	0.307	0.378	0.058
	Medium	0.285	0.512	<0.0005	0.239	0.321	0.017
	High	0.310	0.558	<0.0005	0.399	0.465	0.229
Mean of mean distance headways	Low	66.0	52.0	0.009	55.5	56.2	0.852
	Medium	46.7	38.4	0.003	43.3	41.2	0.350
	High	27.8	20.1	<0.0005	19.8	23.2	0.089
Mean of standard deviation of distance head.	Low	8.31	10.8	0.283	8.09	6.89	0.252
	Medium	6.09	8.54	0.069	4.56	4.94	0.643
	High	4.18	5.15	0.291	2.87	3.96	0.113
Mean of mean relative speeds	Low	-7.40	-5.74	0.569	-3.19	-3.95	0.759
	Medium	-1.14	-1.03	0.961	-1.28	-1.14	0.501
	High	-2.76	-2.51	0.825	-0.720	0.407	0.272
Mean of standard deviation of relative speeds	Low	5.19	7.23	0.058	3.78	5.37	0.020
	Medium	3.47	4.76	0.019	2.53	2.83	0.418
	High	4.07	3.69	0.656	2.90	4.01	0.032

3.7 Statistical analysis of adaptations in driver behaviour characteristics when drivers resume manual control

Multiple control transitions and repeated 1 s-observations over a 20 s-time interval for each transition are available for each driver (panel data, Figure 3.6). To analyse the impact of several within-subjects factors simultaneously (e.g., time period, traffic density, ACC system state) on the mean driver behaviour characteristics capturing between-subjects variations and correlations between observations over time for the same subject, linear mixed-effects models for repeated measures containing fixed and random effects were estimated. Linear mixed-effects models are preferred to alternative analyses of repeated measures because they are robust to missing data (e.g., distance headway and relative speed are missing when a leader is not detected by the radar), and they allow to define explicitly a hierarchical structure (correlations between observations for the same driver) and a residual variance-covariance structure (correlations between consecutive observations over time).

The data analysis technique proposed aims at capturing explicitly the duration of adaptation effects in the mean values of each driver behaviour characteristic in different traffic conditions. Notably, the scope of this analysis is merely descriptive. The specification of the fixed effects was selected based on the research hypotheses H_1 and H_2, while the specification of the random effects and of the residual variance-covariance matrix were chosen based on the hierarchical structure of the data and statistical significance. Selecting the most appropriate random effects and variance-covariance structure is fundamental for obtaining consistent estimates of the fixed effects and covariance parameters. Pairwise comparisons of the estimated marginal means were calculated to identify the *duration* and *magnitude* of significant changes in the driver behaviour characteristics over time (*transition periods*) when drivers resume manual control (I or AAc, H_1) and at different traffic densities (H_2).

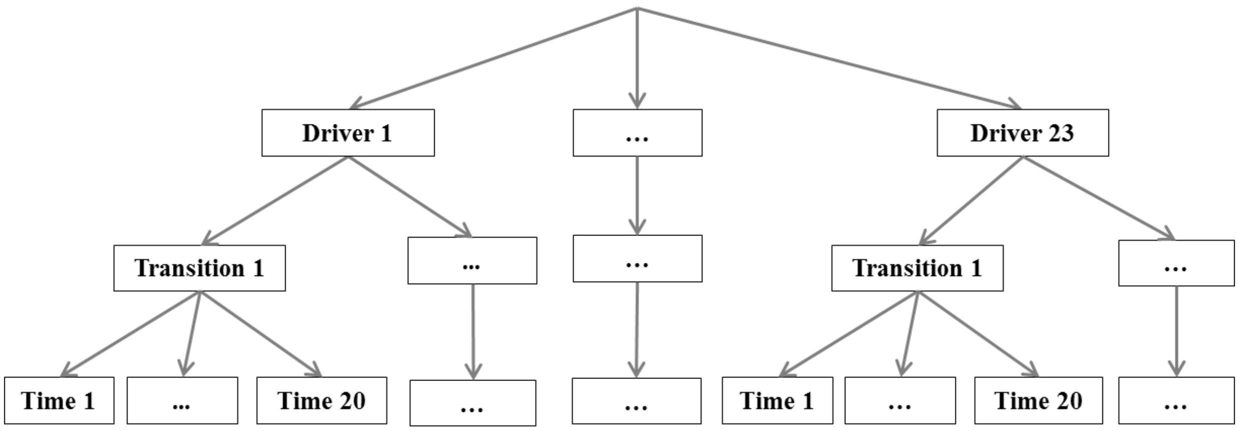


Figure 3.6: Multi-level structure of the driver behaviour data.

3.7.1 Linear mixed-effects models

The linear mixed-effects models (8 in total) were estimated separately for each type of control transition and driver behaviour characteristic. Time period (20 levels), traffic density (3 levels) and ACC system state (3 levels) are defined as categorical explanatory variables to analyse the mean response of drivers over time in each traffic density level, controlling for possible interactions between time, system state and traffic density. Notably, this specification captures explicitly adaptations in driver behaviour characteristics over the 20 s-time interval assuming that the mean response varies every 1 s (i.e., the means are time-specific as described in Steele (2014), pp. 29-31). This time duration (1 s) was chosen because it is similar to the mean reaction time between the recognition of a stimulus and the execution of the response in literature (Toledo, 2003). The driver behaviour characteristic (*DriBeChar*) *Speed, Acceleration, ln(Distance headway)* (front bumper to rear bumper), and *Relative speed* (speed of the leader minus speed of the ego) for driver *n,* transition *Tr*, and time *t* (t=1, …, 20) are given by equation (3.1):

$$
\begin{aligned}
\mathrm{DriBeChar}_{n,Tr}(t) = {} & \alpha + \beta_{Time}(t) \cdot \mathrm{Time}_{Tr}(t) + \sum_{i=1}^{3} \beta^{i}_{SystSta} \cdot \mathrm{SystSta}^{i}_{Tr}(t) \\
& + \sum_{k=1}^{3} \beta^{k}_{Dens} \cdot \mathrm{Dens}^{k}_{Tr} + \sum_{i=1}^{3} \beta^{i}_{SystSta\cdot Time}(t) \cdot \mathrm{SystSta}^{i}_{Tr}(t) \cdot \mathrm{Time}_{Tr}(t) \\
& + \sum_{i=1,\,k=1}^{3,\,3} \beta^{i,k}_{SystSta\cdot Dens\cdot Time}(t) \cdot \mathrm{SystSta}^{i}_{Tr}(t) \cdot \mathrm{Dens}^{k}_{Tr} \cdot \mathrm{Time}_{Tr}(t) \\
& + \gamma \cdot \vartheta_n + \sigma \cdot \varepsilon_{n,Tr}(t)
\end{aligned}
\tag{3.1}
$$

Where

α	is the intercept (mean);
β	are the parameters associated with each level of the categorical explanatory variables;
$\mathrm{Time}_{Tr}(t)$	is a dummy variable denoting the time *t* (t=1, …, 20);
$\mathrm{SystSta}^{i}_{Tr}(t)$	is a dummy variable equal to 1 when the ACC system state is equal to $\mathrm{SystSta}^{i}\in$\{Inactive, Active, Active and accelerate\}, for i=1,2,3;
Dens^{k}_{Tr}	is a dummy variable equal to 1 when the level of traffic density is equal to $\mathrm{Dens}^{k}\in$\{Low density, Medium density, High density\}, for k=1,2,3;
γ	is the parameter (between drivers variance) associated with the driver-specific error term ϑ_n~N(0,1);
σ	is the parameter (between observations variance) associated with the observation-specific error term (residual) $\varepsilon_{n,Tr}(t)$,

$$
\boldsymbol{\varepsilon}_{\mathbf{n,Tr}}=\begin{bmatrix} \varepsilon_{n,Tr}(1) \\ \\ \vdots \\ \varepsilon_{n,Tr}(20) \end{bmatrix} \sim N\left(0,\boldsymbol{\Lambda}_{\mathbf{n,Tr}}\right), \quad \boldsymbol{\Lambda}_{\mathbf{n,Tr}}=\begin{bmatrix} 1 & \rho\cdot\varphi & \rho^2\cdot\varphi & \cdots & \rho^{19}\cdot\varphi \\ \rho\cdot\varphi & 1 & \rho\cdot\varphi & \cdots & \rho^{18}\cdot\varphi \\ \rho^2\cdot\varphi & \rho\cdot\varphi & 1 & \cdots & \rho^{17}\cdot\varphi \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho^{19}\cdot\varphi & \rho^{18}\cdot\varphi & \rho^{17}\cdot\varphi & \cdots & 1 \end{bmatrix}
$$

The distributions of speed, acceleration and relative speed were assumed to follow the normal probability density function. The log-normal probability density function was found to best fit the distance headway distributions based on goodness-of-fit measures (log likelihood). For model estimation, the parameters associated with one level of each categorical explanatory variable have been normalized to zero. Alternative specifications of the fixed effects were explored including factors such as experience with ACC and lane changes, which had a non-significant effect on the mean driver behaviour characteristics.

Responses for different subjects are assumed to be independent. Unobserved preferences that influence all driver behaviour characteristics of the same individual driver are captured by the driver-specific error term ϑ_n (random effect). To account for the serial correlation between 1 s-measurements over the 20 s-time interval in each control transition (repeated effects), the residual covariance structure $\mathbf{\Lambda_{n,Tr}}$ is specified as a first-order autoregressive moving-average ARMA(1,1) (Box et al., 2013; Pinheiro and Bates, 2000). The autoregressive parameter ρ captures the decline in correlations between observations with increasing time-lag and the moving-average parameter φ captures constant correlations over the 20 s-time interval. This structure has been selected based on goodness-of-fit measures (log likelihood) and information criteria (AIC, BIC). Alternative specifications of the residual covariance matrix (e.g., unstructured) were explored but, controlling for the number of parameters estimated, did not result in a significant improvement in goodness of fit.

3.7.2 Pairwise comparisons of the estimated marginal means

The ‘Mixed Model’ command in SPSS 24 (IBM Corporation, 2016) was used for model estimation. The estimation method chosen was the restricted maximum-likelihood (REML), which provides unbiased estimators of the variance components accounting for the degrees of freedom used to estimate the fixed effects (Verbeke and Molenberghs, 2009; Zuur et al., 2009). The parameters estimated were used to calculate the marginal means of the driver behaviour characteristics over time in each traffic conditions controlling for the system state, between-subjects variation and residual covariance structure. Pairwise comparisons were used to test statistically the hypothesis of significant changes in the mean driver behaviour characteristics over time when drivers are in control of the vehicle (I or AAc) in different traffic flow conditions. Mean values at time *t* were compared to mean values at time *t+1*. Significant changes in each second over a certain interval of time after the ACC system was deactivated or overruled by pressing the gas pedal can be interpreted as an indicator of the time duration needed to stabilize driving behaviour after resuming manual control (*transition period*, similar to Merat et al. (2014)). The *magnitude* of the corresponding adaptation in driver behaviour characteristics was calculated using the model. The advantage of this data analysis technique is to quantify the transition period explicitly based on significant changes in the driver behaviour characteristics. The final results are robust to the initial choice of the 20-s time interval for each transition.

3.8 Estimation results

Table 3.4 and Table 3.5 present the tests of fixed effects and of covariance parameters of the linear mixed-effects models for each dependent variable and transition type. These tests show which factors influence each driver behaviour characteristic during control transitions. Estimates of fixed effects are tested using F-tests, which allow identifying the impact of each single factor on the driver behaviour characteristics. Estimates of covariance parameters ρ and φ are tested using two tailed Wald z-tests (i.e. the parameters can be positive or negative), while estimates of variance parameters are tested using one-tailed Wald z-tests (i.e., the variance can be equal to or larger than zero) (Tabachnick and Fidell, 2013). To test the research hypotheses proposed in this study, pairwise comparisons of the estimated marginal means were calculated as described in Section 3.7.2. Reporting the parameters estimated would not contribute to this purpose. The parameters estimated cannot be directly interpreted as unconditional marginal effects due the inclusion of multiplicative interaction terms in the specification of the fixed effects. Figure 3.7 and Figure 3.8 show the estimated marginal means and the confidence intervals of the mean estimates of each driver behaviour characteristic calculated as a function of system state and time in each traffic density level. Notably, the mean profiles show the temporal evolution of driver behaviour characteristics over time at different traffic densities controlling for the confounding effect of other control transitions in the 20-s interval and between-subjects variability. Table 3.6 presents the summary of the estimated marginal means analysis in terms of transition period and corresponding adaptation in driver behaviour characteristics when the driver controlled the vehicle at low, medium and high traffic densities. These results represent the primary focus of the current study.

3.8.1 Adaptations in transition to Inactive (DIDC)

The linear mixed-effects models (Table 3.4) indicated a significant main effect of time and of traffic density on all driver behaviour characteristics, and of system state on accelerations. The interaction terms of time and system state and of time, system state and traffic density did not have a significant impact on all driver behaviour characteristics. These results mean that the driver behaviour characteristics change significantly over time and these changes do not differ significantly between traffic density levels. The driver-specific error terms were not significant (distance headways: p-value =0.056), meaning that the driver behaviour characteristics do not differ significantly between drivers. The residual covariance parameters were significant, suggesting that, controlled for the fixed effects, the mean driver behaviour characteristics differ significantly between observations (sigma) and are significantly correlated over the 20-s time intervals (rho and phi).

Figure 3.7 shows the profiles of the mean driver behaviour characteristics, which are consistent with the empirical findings in Figure 3.4. Pairwise comparisons showed that, when the system was I, the speed was significantly higher than the speed in the following observation in each second in the interval 0-9 s after the transition (0-1 s to 8-9 s: p-value <0.0005), meaning that the speed decreases significantly. This duration indicates the time drivers need to stabilize the speed (transition period, Table 3.6). The acceleration was significantly higher 0-1 s after the transition than 1-2 s after (p-value <0.0005) and in each second in the interval 1-4 s the acceleration was significantly lower than in the following observations (1-2 s: p-value <0.0005; 2-3 s: p-value <0.0005; 3-4 s: p-value =0.009), meaning that the acceleration decreases for 1 s and then increases significantly. The distance headway was higher in each second in the interval 0-3 s after the transition than in the following observations (0-1 s: p-value <0.0005; 1-2 s: p-value <0.0005; 2-3 s: p-value =0.001), meaning that the mean distance headway significantly decreases after drivers deactivate the system. The relative speed was significantly lower in each second in the interval 0-3 s after the transition than in the following observations (0-1 s, 1-2 s: p-value <0.0005, 2-3 s: p-value =0.001), meaning that the relative speed increases significantly. These results are consistent with the fact that most drivers deactivated the ACC system by braking and then released the brake pedal after few seconds in each traffic condition.

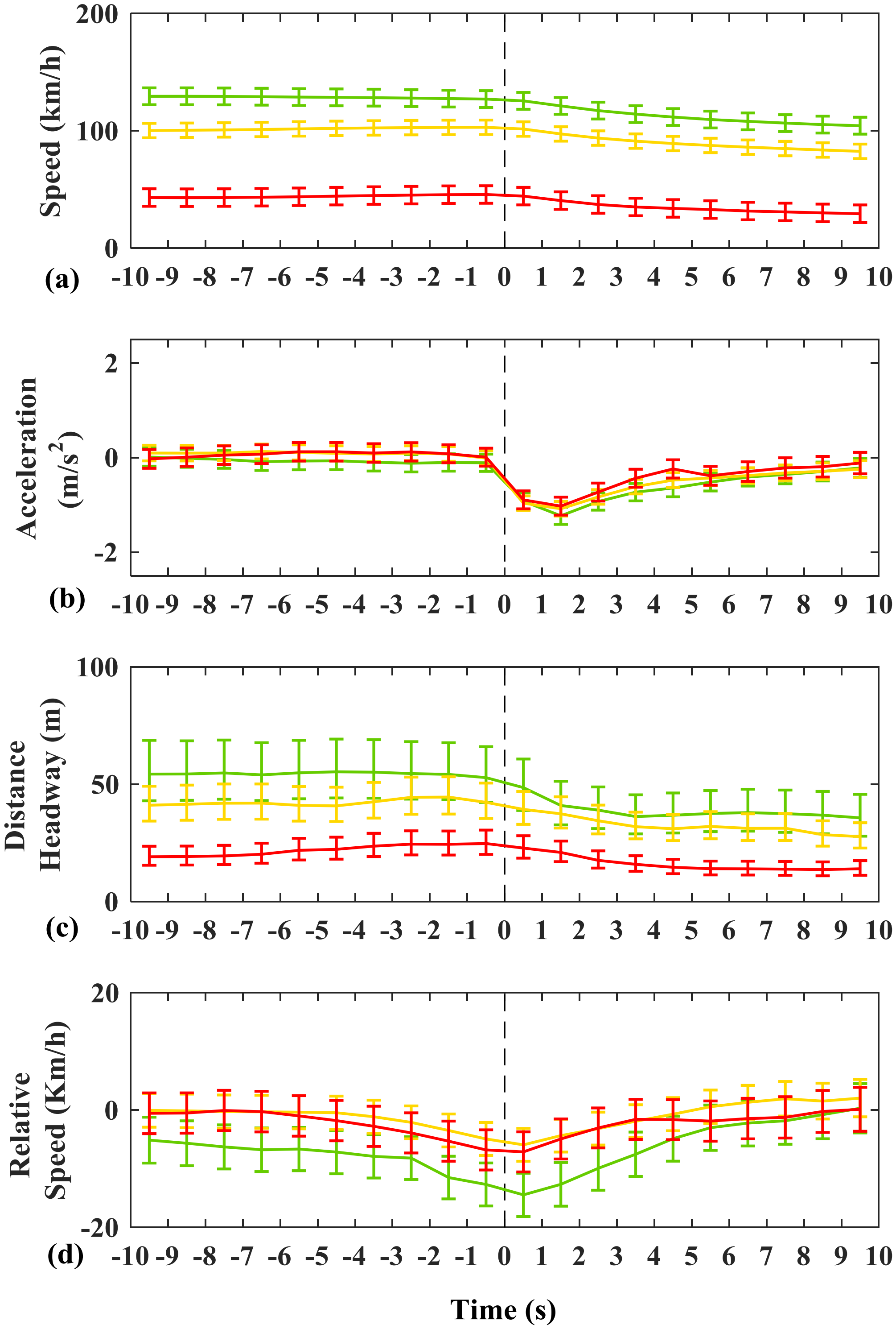


Figure 3.7: Transitions to Inactive (A to I): estimated marginal means (solid line) and 95% confidence intervals of the mean estimates (error bars) of (a) speed, (b) acceleration, (c) distance headway and (d) relative speed calculated as a function of system state and time in the interval 10 s before (-10, 0) and 10 s after (0, 10) the instant when the transition is initiated (dashed black line).

Note: Green lines represent low density conditions (0-11 veh/km/lane), yellow lines medium density conditions (11-22 veh/km/lane), and red lines high density conditions (>22 veh/km/lane).

Table 3.4: Transition to Inactive (A to I): linear mixed-effects models for empirical adaptation effects in driver behaviour

	Fixed Effects	df	Error	F	p-value
Speed	Intercept	1	16.46	1850.59	<0.0005
	Time	19	1936.72	56.30	<0.0005
	Density	2	110.89	133.23	<0.0005
	System state	2	2149.46	1.43	0.239
	Time*System state	31	1599.19	1.22	0.187
	Time*System state*Density	85	1500.17	1.03	0.415
	Covariance parameters			Wald Z	p-value
	Gamma (var. between driv.)			0.01	0.496
	Sigma (var. between obs.)			7.33	<0.0005
	Rho (autoregressive)			1151.35	<0.0005
	Phi (moving-average)			2301.07	<0.0005
Acceleration	Fixed Effects	df	Error	F	p-value
	Intercept	1	740.21	13.55	<0.0005
	Time	19	1547.78	8.29	<0.0005
	Density	2	563.93	4.44	0.012
	System state	2	1968.06	8.93	<0.0005
	Time*System state	31	1507.33	0.91	0.604
	Time*System state*Density	85	1379.54	0.94	0.643
	Covariance parameters			Wald Z	p-value
	Gamma (var. between driv.)			-	-
	Sigma (var. between obs.)			20.41	<0.0005
	Rho (autoregressive)			34.21	<0.0005
	Phi (moving-average)			79.09	<0.0005
Ln(Distance headway)	Fixed Effects	df	Error	F	p-value
	Intercept	1	26.78	3190.59	<0.0005
	Time	19	1356.99	5.29	<0.0005
	Density	2	154.82	37.55	<0.0005
	System state	2	1594.31	1.73	0.177
	Time*System state	31	1337.59	1.03	0.425
	Time*System state*Density	84	1242.33	1.24	0.077
	Covariance parameters			Wald Z	p-value
	Gamma (var. between driv.)			1.59	0.056
	Sigma (var. between obs.)			10.37	<0.0005
	Rho (autoregressive)			108.85	<0.0005
	Phi (moving-average)			176.71	<0.0005
Relative speed	Fixed Effects	df	Error	F	p-value
	Intercept	1	25.31	14.71	0.001
	Time	19	1373.78	5.04	<0.0005
	Density	2	153.01	3.23	0.042
	System state	2	1658.32	0.08	0.924
	Time*System state	31	1323.34	0.61	0.955
	Time*System state*Density	84	1208.22	0.82	0.879
	Covariance parameters			Wald Z	p-value
	Gamma (var. between driv.)			0.20	0.420
	Sigma (var. between obs.)			11.16	<0.0005
	Rho (autoregressive)			87.84	<0.0005
	Phi (moving-average)			158.99	<0.0005

Note: df denotes the degrees of freedom, F the statistics of the F test, Wald Z the statistics of the Wald Z test.

3.8.2 Adaptations in transition to Active and Accelerate (DIDC)

The linear mixed-effects models (Table 3.5) indicated significant main effects of time and of system state on all driver behaviour characteristics, and of traffic density on speed, distance headway and relative speed. The interaction terms of time, system state and traffic density had a significant effect on all driver behaviour characteristics. These results mean that the driver behaviour characteristics change significantly over time and these changes differ significantly between traffic density levels. The driver-specific error term had a significant impact on relative speeds, meaning that relative speeds differ significantly between drivers. The residual covariance parameters were significant, suggesting that, controlled for the fixed effects, the mean driver behaviour characteristics differ significantly between observations (sigma) and are significantly correlated over the 20-s time intervals (rho and phi).

Figure 3.8 shows the profiles of the mean driver behaviour characteristics, which are consistent with the empirical results in Figure 3.5. Pairwise comparisons showed that, when the system was AAc, in each second in the interval 1-5 s after the transition at low densities (1-2 s: p-value =0.014, 2-3 s to 4-5 s: p-value <0.0005), 1-3 s after the transition at medium densities (1-2 s: p-value <0.0005; 2-3 s: p-value =0.011), and 0–5 s after the transition at high densities (0-1 s: p-value =0.001; 1-2 s to 3-4 s: p-value <0.0005; 4-5 s: p-value =0.024) the speed was significantly lower than in the following observations, meaning that the speed increased significantly. This duration indicates the time need to stabilize the speed (transition period, Table 3.6). The acceleration was significantly lower 0-1 s after the transition than 1-2 s after (p-value <0.0005) at low, medium and high densities, meaning that the acceleration increased significantly. The distance headway was significantly lower 0-1 s after the transition than 1-2 s after at low (p-value =0.006) and high densities (p-value =0.008), meaning that it increased significantly. Pairwise comparisons showed non-significant results on relative speeds when the system was AAc after the transition. These results are consistent with the fact that drivers pressed the gas pedal and then released the gas pedal after few seconds.

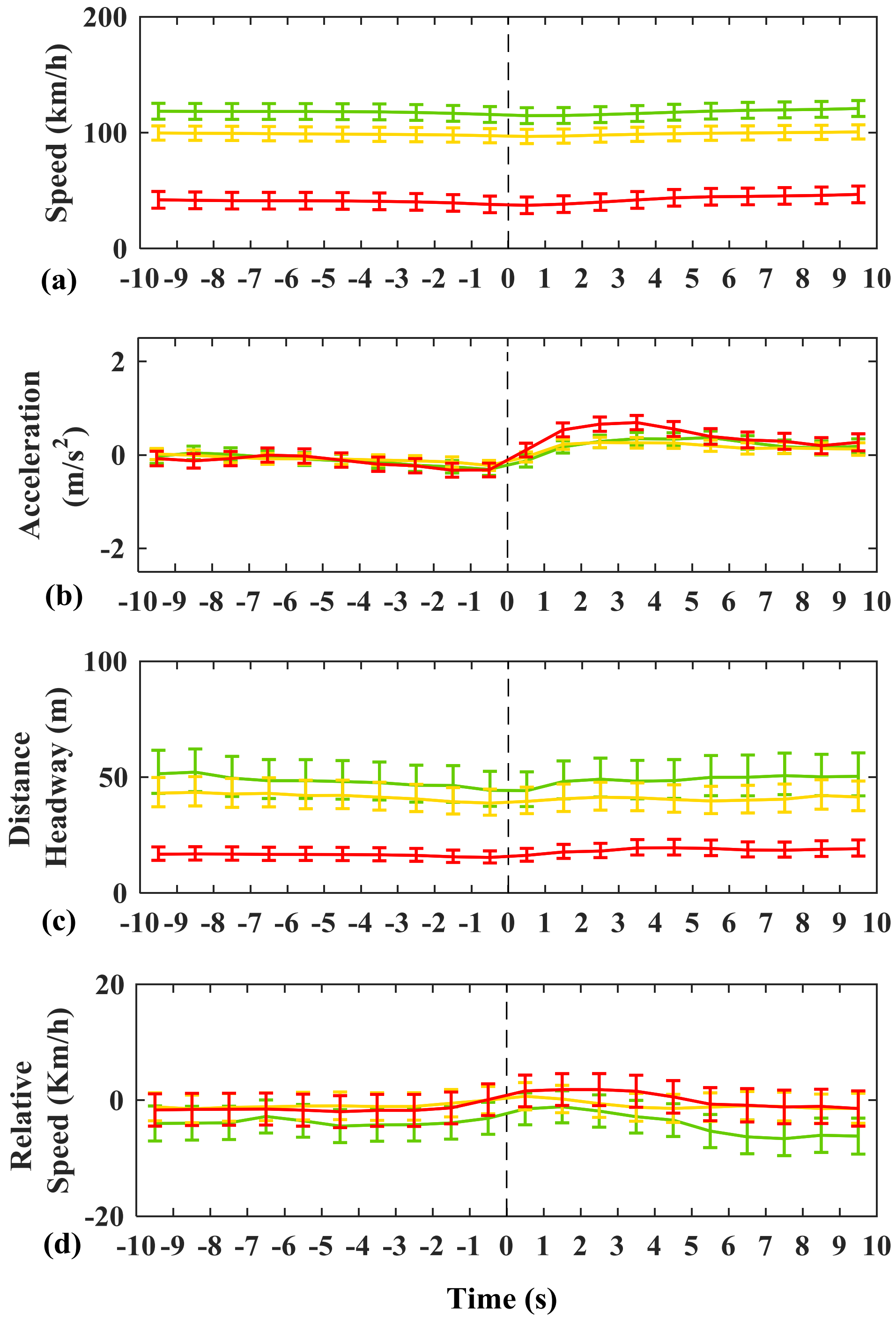


Figure 3.8: Transitions to Active and accelerate (A to AAc): estimated marginal means (solid line) and 95% confidence intervals of the mean estimates (error bars) of (a) speed, (b) acceleration, (c) distance headway and (d) relative speed calculated as a function of system state and time in the interval 10 s before (-10, 0) and 10 s after (0, 10) the instant when the transition is initiated (dashed black line).

Note: Green lines represent low density conditions (0-11 veh/km/lane), yellow lines medium density conditions (11-22 veh/km/lane), and red lines high density conditions (>22 veh/km/lane).

Table 3.5: Transition to Active and Accelerate (A to AAc): linear mixed-effects models for empirical adaptation effects in driver behaviour

	Fixed Effects	df	Error	F	p-value
Speed	Intercept	1	18.69	1366.14	<0.0005
	Time	19	3247.93	12.93	<0.0005
	Density	2	177.32	168.39	<0.0005
	System state	2	2664.88	10.41	<0.0005
	Time*System state	38	1811.64	4.17	<0.0005
	Time*System state*Density	112	2078.50	1.46	0.001
	Covariance parameters			Wald Z	p-value
	Gamma (var. between driv.)			1.57	0.059
	Sigma (var. between obs.)			10.18	<0.0005
	Rho (autoregressive)			1959.96	<0.0005
	Phi (moving-average)			3923.10	<0.0005
	Fixed Effects	df	Error	F	p-value
Acceleration	Intercept	1	20.74	5.95	0.024
	Time	19	2324.19	4.09	<0.0005
	Density	2	205.58	1.53	0.220
	System state	2	3531.06	147.93	<0.0005
	Time*System state	38	2409.02	2.63	<0.0005
	Time*System state*Density	112	2535.20	2.43	<0.0005
	Covariance parameters			Wald Z	p-value
	Gamma (var. between driv.)			0.82	0.206
	Sigma (var. between obs.)			22.87	<0.0005
	Rho (autoregressive)			60.40	<0.0005
	Phi (moving-average)			126.14	<0.0005
	Fixed Effects	df	Error	F	p-value
Ln(Distance headway)	Intercept	1	13.48	4528.70	<0.0005
	Time	19	2109.85	4.01	<0.0005
	Density	2	192.94	72.88	<0.0005
	System state	2	2974.21	11.77	<0.0005
	Time*System state	38	2165.10	1.91	0.001
	Time*System state*Density	112	2185.09	1.26	0.039
	Covariance parameters			Wald Z	p-value
	Gamma (var. between driv.)			1.32	0.093
	Sigma (var. between obs.)			12.75	<0.0005
	Rho (autoregressive)			203.86	<0.0005
	Phi (moving-average)			345.89	<0.0005
	Fixed Effects	df	Error	F	p-value
Relative speed	Intercept	1	19.36	7.14	0.015
	Time	19	2057.97	2.69	<0.0005
	Density	2	233.74	5.13	0.007
	System state	2	3006.63	8.04	<0.0005
	Time*System state	38	2149.53	1.43	0.044
	Time*System state*Density	112	2171.00	1.97	<0.0005
	Covariance parameters			Wald Z	p-value
	Gamma (var. between driv.)			2.02	0.022
	Sigma (var. between obs.)			14.66	<0.0005
	Rho (autoregressive)			116.97	<0.0005
	Phi (moving-average)			207.22	<0.0005

Note: df denotes the degrees of freedom, F the statistics of the F-test, Wald Z the statistics of the Wald Z test.

Table 3.6: Transition periods (TP) and corresponding adaptations in driver behaviour characteristics (DBC) in transitions to Inactive (A to I) and to Active and accelerate (A to AAc)

DBC	Density level	I (after A to I)				AAc (after A to AAc)			
		TP (s)	DBC_i	DBC_f	ΔDBC	TP (s)	DBC_i	DBC_f	ΔDBC
Speed (km/h)	Low	8	126	105	-20.2	5	115	119	3.90
	Med.	9	102	82.6	-19.0	3	97.8	98.6	1.20
	High	4	44.4	33.9	-10.5	5	37.3	44.7	6.50
Accelera-tion (m/s^2)	Low	1	-0.923	-1.23	-0.309	1	-0.128	0.173	0.301
		1	-1.23	-0.930	+0.302				
	Med.	1	-0.964	-1.08	-0.118	1	-0.044	0.227	0.271
		2	-1.08	-0.614	+0.469				
	High	1	-0.895	-1.03	-0.133	1	0.104	0.536	0.432
		2	-1.03	-0.437	+0.590				
Distance headway (m)	Low	1	48.6	40.9	-7.63	1	44.1	48.1	3.99
	Med.	NS	NS	NS	NS	NS	NS	NS	NS
	High	2	22.8	17.6	-5.23	1	16.3	17.7	1.46
Relative speed (km/h)	Low	4	-14.4	-4.87	9.57	NS	NS	NS	NS
	Med.	NS	NS	NS	NS	NS	NS	NS	NS
	High	NS	NS	NS	NS	NS	NS	NS	NS

Note: DBC_i denotes the driver behaviour characteristic at the beginning of the transition period, DBC_f at the end, and ΔDBC the adaptation in the driver behaviour characteristics during the transition period; NS indicates non-significant results.

3.9 Conclusions and future research

This study has analysed adaptations in speed, acceleration, distance headway, and relative speed a few seconds after drivers deactivated or overruled the full-range ACC. To the best of the author's knowledge, this is one of the first studies capturing explicitly the duration (*transition period*) and the magnitude of significant changes in these driver behaviour characteristics over time in non-critical traffic situations based on data collected in an on-road experiment. The on-road experiment was designed to control for potentially confounding factors such as road design and traffic conditions which are common limitations of FOTs and naturalistic studies. Twenty-three participants drove a research vehicle equipped with full-range ACC on a 35.5-km freeway in Munich during peak hours. The average traffic density during the experiment was calculated using loop-detector data.

The statistical analysis method proposed (linear mixed-effects models) is suitable to analyse adaptations in driver behaviour characteristics when drivers resumed manual control, capturing the impact of observable factors, variations between individuals, and correlations between consecutive observations over time. This method explicitly recognizes the hierarchical structure of the data (subjects, control transitions within subjects, observations over time for each transition) and is robust to missing data and unbalanced designs (e.g., different number of repetitions for each driver). Correlations between driver behaviour characteristics of the same individual driver are captured by a driver-specific error term, while correlations between observations over time in each control transition by an ARMA(1,1) residual covariance structure. The parameters estimated were used to calculate the marginal means of the driver behaviour characteristics over time in each traffic condition controlling for the system state, between-subjects variation and residual covariance structure. Pairwise comparisons of the estimated marginal means were calculated to determine the duration and magnitude of significant adaptation effects when drivers are in control of the vehicle in different traffic flow conditions. The results revealed that the time duration after the control transition was initiated, the traffic density and the system state (*Inactive, Active, Active and accelerate)* had a significant impact on speed, acceleration, distance headway and relative speed.

After the ACC system was deactivated, the speed and the distance headway decreased significantly, the acceleration decreased for 1 s and then increased significantly, and the relative speed increased significantly in each traffic condition. At high densities, the speed decreased by 10.5 km/h (from 44.4 to 33.9 km/h) in 4 s after deactivation. Based on theories proposed in driver psychology, these significant speed reductions can be interpreted as a compensation strategy to decrease the feeling of risk and task difficulty (Fuller, 2005, 2011) associated with a complex traffic situation such as preparing to change lane (Pereira et al., 2015), approaching a slower leader (Varotto et al., 2017), approaching areas of increased lane changes as on-ramps (Varotto et al., 2017), expecting vehicles cutting-in (Varotto et al., 2017), and preparing to exit the freeway (Varotto et al., 2017). The transition period can be interpreted as the duration needed to stabilize driving behaviour after the deactivation. All drivers showed a similar compensation strategy when deactivating the system in different traffic situations. Further research is needed to analyse differences between drivers in mean distance headways, which might indicate that some drivers accept higher risks with the system active.

After the ACC was overruled by pressing the gas pedal, the speed and the acceleration increased significantly in each traffic condition. At high densities, the speed increased significantly by 6.50 km/h (from 37.3 to 44.7 km/h) in 5 s after the system was overruled. These significant speed increments can be interpreted as a compensation effect to increase the traffic complexity of a situation as proposed by Pereira et al. (2015), when approaching a faster leader (Varotto et al., 2017) or when preparing a lane change. Significant differences between drivers in terms of relative speeds during control transitions to Active and accelerate suggest that certain drivers overrule the system when the differences in speeds are smaller. In contrast with transitions to Inactive, the adaptation effects in driver behaviour characteristics differed significantly between traffic conditions. Drivers showed the largest accelerations and speed increments after overruling the system at high densities.

The main conclusion from this study is that driver behaviour characteristics change significantly over time when drivers deactivate the full-range ACC or overrule it by pressing the gas pedal. The duration and magnitude of these adaptions can be quantified by using linear mixed-effects models, which are suitable to control for observable and unobservable factors. These adaptations can be interpreted as a compensation strategy to decrease (or increase) the feeling of risk and task difficulty experienced. This study presents a descriptive analysis of the driver behaviour characteristics during control transitions and further analysis is needed to develop a driver behaviour model. Nonetheless, the findings provide an empirical foundation for developing human-like driving assistance systems that are acceptable for drivers in a wider range of situations and more realistic microscopic traffic flow models that account for driver interaction with ACC in different traffic conditions.

Driving assistance systems that mimic human driving style are needed to enhance comfort and acceptability (Bifulco et al., 2013; Goodrich and Boer, 2003). The results in this study suggest that drivers could maintain the ACC active if the system decreased the speed, while guaranteeing safety and comfort, in traffic situations in which they are likely to deactivate. Similarly, drivers could maintain the ACC active if the system increased the speed in situations in which they are likely to overrule the system by pressing the gas pedal. The choice model developed in a previous study can be implemented into these new systems to identify the situations in which drivers are likely to resume manual control (Varotto et al., 2017).

Microscopic traffic flow models that capture the empirical findings in this study are needed to assess accurately the impacts of full-range ACC on traffic flow efficiency and safety. Current car-following models should be advanced to forecast the conditions in which drivers transfer control (Varotto et al., 2017) and to mimic the response of manual drivers during control transitions. Based on the empirical insights in this study and theories of driver behaviour, future research can focus on developing a novel model framework grounded on feeling of risk and task difficulty. In this framework, the vehicle acceleration can be specified explicitly as a function of two additive terms, the first one representing regular car-following behaviour and the second one representing adaptations in control transitions (similar to the advanced car-following models capturing compensation effects at sags by Goni-Ros et al. (2016), and capturing driver distraction by Hoogendoorn et al. (2013) and by Saifuzzaman et al. (2015)). For instance, the second term can be specified as a function of the transition period and the corresponding speed change described in this study. Implementing this advanced car-following model into a microscopic traffic flow simulation, the impact of transitions from ACC to manual control on capacity, capacity drop and string stability can be investigated more realistically than in current traffic flow simulations. The significant speed decrement after the system was deactivated and the significant speed increment after the system was overruled can, for instance, result in string instability at high penetration rates of ACC vehicles.

Future research is required to gain a deeper insight into driver behaviour during transitions to manual control. The statistical analysis methods proposed in this study can be used to investigate the impact of other explanatory factors on adaptations in driver behaviour characteristics, such as lane changes, driver characteristics (e.g., experience with the ACC system and driving styles), and characteristics of the freeway segment. The model proposed, however, can control for the impact of a limited number of factors simultaneously with the interaction of time (20 levels), depending on the number of observations available. Physiological measurements capturing driver workload and situation awareness can be analysed to shed light on the origin of these adaptation effects in driver behaviour characteristics (De Winter et al., 2014). Finally, the findings in this study are dependent on the characteristics of the ACC system tested and further analysis is needed to assess their generalisability to other driving assistance systems and to higher levels of vehicle automation. Adaptation effects are likely to increase for higher levels of automation, when the system controls both the lateral and the longitudinal control task (SAE Levels 2-4) and drivers are expected to monitor the surrounding environment only in specific circumstances (SAE Level 3-4).

II Modelling decisions of control transitions

Chapter 4

Factors influencing decisions of control transitions in full-range Adaptive Cruise Control

FOTs have found that drivers may prefer to deactivate ACC in dense traffic flow conditions and before changing lanes. Results in Chapter 2 indicated that drivers may differ in their decisions to activate and to deactivate the ACC system in similar traffic situations. However, most of the models currently used to evaluate the impact of ACC do not describe control transitions. A few mathematical models have proposed deterministic decision rules for transferring control, ignoring heterogeneity between and within drivers in the decision-making process.

This chapter analyses the main factors that influence drivers' decisions to deactivate the full-range ACC or overruled it by pressing the gas pedal (DIDC transitions), based on a dataset collected in an on-road experiment. The chapter is structured as follows. Section 4.1 introduces drivers' decisions of control transitions with ACC. Section 4.2 discusses existing models for control transitions and their limitations. Section 4.3 provides an overview of the controlled on-road experiment with full-range ACC (for a detailed description, refer to Chapter 3). Section 4.4 explores the relations between drivers' decisions to resume manual control and driver behaviour characteristics, driver characteristics, and road characteristics. Section 4.5 presents a mixed logit model that predicts the choices to deactivate the system or overrule it by pressing the gas pedal. Finally, Section 4.6 discusses the main factors influencing transitions to manual control and directions for future research.

This chapter is an edited version of the following paper:

Varotto, S.F., Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2017. Resuming manual control or not? Modelling choices of control transitions in full-range Adaptive Cruise Control. *Transportation Research Record: Journal of the Transportation Research Board* 2622, 38-47.

http://dx.doi.org/10.3141/2622-04

NOTE: The original paper was subject to minor textual revision and a validation analysis of the choice model estimated was included in Appendix A.

4.1 Introduction

Automated vehicles and driving assistance systems can contribute to reduce congestion, accidents, and levels of emissions. Automated vehicles may increase roadway capacity, improve traffic flow stability, and speed up the outflow from a queue (Hoogendoorn et al., 2014). The functionalities of automated systems are gradually introduced into the market, such as in the case of Adaptive Cruise Control (ACC). The ACC is designed to maintain a desired speed and time headway, therefore influencing substantially the performance of the driving task. The impact of ACC systems on driving behaviour has been extensively analysed since the 1990s, primarily in driving simulator experiments. Field Operational Tests (FOTs) have shown potential safety benefits of ACC systems which are inactive at low speeds when they are activated: drivers maintain larger time headways (Alkim et al., 2007; Gorter, 2015; Malta et al., 2012; NHTSA, 2005), follow the leader twice as long as in manual driving (NHTSA, 2005), and prepare lane changes in advance to refrain from interactions with slower vehicles (Alkim et al., 2007). A possible explanation for these behavioural adaptations is that, when the ACC is active, drivers do not manually control the vehicle (Hoogendoorn et al., 2014). These findings, however, might be biased by the circumstances in which the system is engaged (e.g., medium-high speeds, medium-light traffic and non-critical conditions).

In certain traffic situations, drivers may prefer to deactivate the system and resume manual control, or the system deactivates because of its functioning limitations. These transitions between automation and manual driving are called control transitions (Lu et al., 2016) and may have a significant impact on traffic flow efficiency (Varotto et al., 2015) and safety (Vlakveld et al., 2015). The characteristics of the ACC, the road, traffic flow, and the drivers affect the initiation of these transitions (Varotto et al., 2014). FOTs have shown that dense traffic conditions (NHTSA, 2005; Viti et al., 2008) and manoeuvres such as lane changing may influence drivers' decision to disengage ACC systems that are inactive at low speeds. Recently, these functioning limitations have been overcome by the introduction of *full-range* ACC systems that can operate in stop-and-go conditions. Full-range ACC has been shown to positively impact traffic flow efficiency (Van Driel and Van Arem, 2010). To quantify this effect at varying penetration rates, mathematical models of manually driven and automated vehicles should be developed and implemented into microscopic traffic simulation models. However, most current car-following and lane changing models do not account for these control transitions. A few microscopic traffic flow models (Klunder et al., 2009; Van Arem et al., 1997) have implemented deterministic decision rules for transferring control between ACC and manual driving, ignoring heterogeneity between and within drivers in the decision-making process. Thus, the impacts on traffic flow predicted by these models could be misleading.

This study explores the factors that influence transitions from full-range ACC to manual control. A mixed logit model for this transition choice is estimated using a dataset collected in a controlled on-road experiment.

4.2 Literature review

This section reviews available behavioural theories and models for control transitions between ACC and manual driving, based on on-road studies in real traffic (for a review of data collection methods, refer to Carsten et al. (2013)). Notably, transitions of control between ACC and manual driving in safety-critical situations and automation failures have also been investigated in driving simulator experiments with a high degree of controllability (for a review, refer to Varotto et al. (2015)).

Control transitions can be initiated by the driver voluntarily or by the automated system because of its own functioning limitations. Lu et al. (2016) proposed a classification of transitions of control based on who (driver or automation) initiates the transition and who is in control afterwards. Therefore, transitions are defined as ‘Driver Initiates transition, and Driver in Control after’ (DIDC) when drivers deactivate the system, ‘Driver Initiates transition, and Automation in Control after’ (DIAC) when drivers activate it, and ‘Automation Initiates transition, and Driver in Control after’ (AIDC) when the system disengages because of its functioning limitations. The circumstances in which these transitions occur appear to be strongly related to the characteristics of the driver support system. Several FOTs (Alkim et al., 2007; NHTSA, 2005; Viti et al., 2008; Xiong and Boyle, 2012) have investigated driving behaviour with ACC systems that are inactive at speeds below 30 km/h and have limited decelerations capabilities. DIAC transitions may occur for comfort reasons (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008) in non-critical and non-dense traffic situations (e.g., after entering the freeway (Alkim et al., 2007)). DIDC transitions by braking have been primarily related to safety indicators such as time to collision. Xiong and Boyle (2012) classified events in which ACC decelerates automatically into near-crash, conflict and low-risk cases based on time to collision and distance headway rate. They found that drivers were more likely to resume control by braking in near-crashes (56%) and conflicts (42%), compared to low-risk situations (7%). However, drivers can also resume manual control in situations that ACC is able to manage when the response of the system does not match their expectations (Zheng and McDonald, 2005). Viti et al. (2008) found that most ACC deactivations occurred in non-critical situations: in their study, 65-70% of the deactivations were initiated by braking lightly, 20–25% without braking, and only 5-10% by braking hard. They concluded that drivers transfer to manual control to maintain a constant speed in medium–dense traffic conditions. Other studies (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008) proposed that further reasons to initiate DIDC transitions include preparation to changing lanes, anticipation of vehicles merging into the lane, and avoiding overtaking slower vehicles on the left lanes. AIDC transitions occur when the system fails (e.g., the sensors malfunction) or when the required control exceeds the system limits (e.g., hard braking is needed).

However, control transitions with full-range ACC systems might be initiated in different situations. In a controlled on-road experiment, Pereira et al. (2015) found that DIDC transitions occurred when the vehicle exited the freeway (51% of the deactivations), approached a moving vehicle (13%) and changed lane (13%), and when the leader changed lanes or a vehicle cut in (22%). They also suggested that DIDC transitions by pressing the gas pedal can be seen as a compensation strategy to increase the complexity of a situation considered to be too simple. This study did not find significant learning effects related to control transition behaviour over the duration of the experiment.

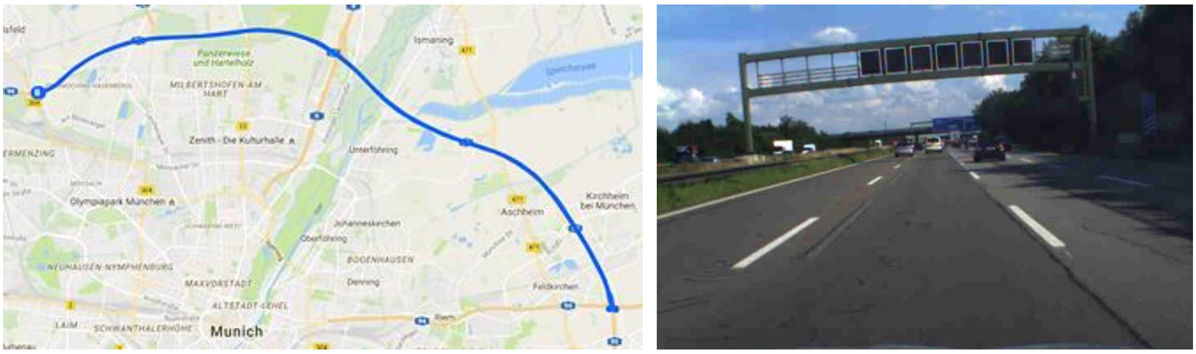
To date, few microscopic traffic flow models have accounted for the possibility of control transitions between ACC and manual driving. Van Arem et al. (1997) developed a microscopic traffic simulation model (MIXIC) in which drivers activated and deactivated the ACC. DIDC are initiated when the situation requires hard braking, when the vehicle approaches a considerably slower leader and when changing lanes. DIAC are initiated when the current acceleration is in the range -0.5 to 0.5 m/s^2, and when the current distance headway allows synchronizing the speed with a deceleration equal to -1 m/s^2. Based on this model and empirical findings (Pauwelussen and Feenstra, 2010; Pauwelussen and Minderhoud, 2008; Viti et al., 2008), Klunder et al. (2009) proposed a microscopic traffic simulation model (ITS Modeler) in which DIDC are initiated when the absolute value of the difference between the desired acceleration and the ACC acceleration is larger than 3.5 m/s^2, and the relative speed between the leader on the left lane and the subject vehicle is larger than 3.0 m/s. AIDC transitions occur when the desired speed or acceleration are outside the range supported by the system (30 to 160 km/h, and -3 to +3 m/s^2). Drivers are assumed to activate the system (DIAC) after it has been inactive for at least 5 s and when both the speed and the acceleration are within the ranges of 36 to 160 km/h, and 0 to 3 m/s^2. The main limitation of these models is that the decisions rules are deterministic: heterogeneity between and within drivers in the decision-making process is ignored.

Xiong and Boyle (2012) estimated a logistic regression model to predict the probability that drivers would brake to initiate a DIDC transition as they closed in on a leader. They included variables that describe the situation and characteristics of the driver in their model. They found that drivers are more likely to intervene in non-highways environments, at lower speeds, and with short gap settings. In addition, middle-aged drivers are more likely to resume manual control than young drivers. However, this model only handles transitions in a narrowly defined set of situations.

In summary, to date, limited efforts have been made to study and model control transitions in a way that would be suitable for implementation in microscopic traffic simulation models. This study presents a mixed logit model predicting the probability of DIDC transitions, both deactivation (by braking or using the on-off button) and overruling (by pressing the gas pedal) of ACC system.

4.3 Data collection

A controlled on-road experiment was conducted using a BMW 5 Series research vehicle equipped with a standard version of full-range ACC. The experiment took place on the section of the A99 freeway in Munich shown in Figure 4.1. The experiment consisted of a single 46-km long drive using different freeway facilities (basic sections, on- and off-ramps) in varying traffic densities. In light traffic conditions, speed limits were not enforced in most of the mainline. In medium-dense traffic conditions, a variable speed limit system recommended a certain speed (120, 100, 80, 60, or 40 km/h) based on real traffic information. The freeway sections were mostly separated 6-lanes. The test route was pre-set in the navigation system. Participants were instructed to try the ACC system and select their preferred gap setting in the first freeway segment. In the rest 35.5 km of the route, they were asked to drive as they would do in real life, regulating the desired speed setting at any time and using the ACC system as they thought it was appropriate. The specifications of the ACC system are described in Section 4.3.1. The sample of participants and the data collection are presented in Section 4.3.2.



(a) (b)

Figure 4.1: A99 in Munich: (a) map (Google Maps, viewed 24 July 2016) and (b) picture of the test route.

4.3.1 ACC system specifications

The ACC system used in the experiment controls the speed in the range between 0 and 210 km/h, and the time headway at speeds above 30 km/h. Drivers can select one of the following target time headways: 1.0, 1.4, 1.8, and 2.2 s. The ACC supports an acceleration range between -3 m/s^2 and $+3$ m/s^2, and the response sensitivity cannot be customized in terms of acceleration characteristics. When the radar (120 m range) does not detect any leader, the system maintains the target speed as a conventional cruise control system. Figure 4.2 shows the three states the system can be in (*Inactive, Active, Active and accelerate*) and the transitions between them. When the system is Inactive, it can be activated by pressing the on/off button, the target speed setting switch, or the resume button. When the system is Active, it can be deactivated by pressing the on/off button or by braking (to Inactive), and temporary overruled by pressing the gas pedal (to Active and accelerate). When the gas pedal is released, the system transfers back to Active.

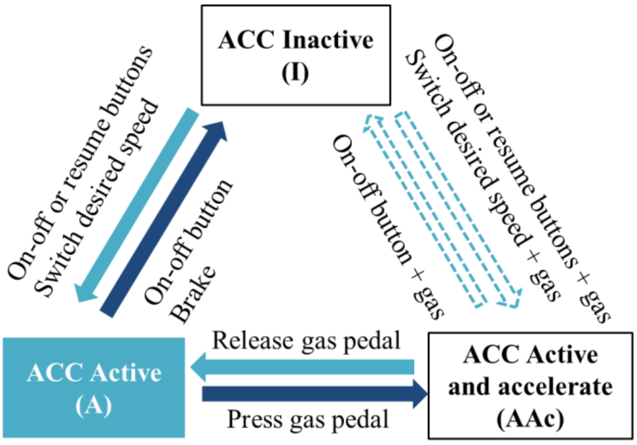


Figure 4.2: ACC system specifications.

Note: White boxes represent system states in which drivers are in control and light blue boxes states in which ACC is in control. Solid arrows denote driver initiated control transitions between ACC system states and dashed arrows state transitions. Light blue solid arrows define DIAC transitions, blue solid arrows DIDC transitions.

4.3.2 Participants and data collection

Twenty-three participants (15 males, 8 females) were recruited among BMW employees who were not involved in the development of the system. Their age ranged between 25 and 51 years old (M = 31.57, SD = 6.73), and their driving experience between 3 and 33 years (M = 13.04, SD = 7.16). Six participants had no experience with ACC, nine were used to drive with ACC less than once a month and eight more often than once a month. Participants received written instructions on the general scope of the research, the ACC system specifications, and the potential safety risks. Notably, the precise aim of the experiment (i.e., investigating driving behaviour in control transitions) was not disclosed and a written informed consent was signed.

The experiment was conducted during morning and evening peak hours (7-9 am, 4-6 pm, 6-8 pm) from June, 29th to July, 9th 2015. Participants were assigned to one of the above-mentioned time slots and drove between 45 and 90 minutes depending on the traffic conditions. The instrumented vehicle recorded the ACC system settings and state, GPS position, speed, acceleration, leader distance headway (from radar), and leader speed and acceleration (from radar). The data were synchronized and recorded at a frequency of 50 Hz (e.g., speed and acceleration of the subject vehicle), 15 Hz (e.g., distance headway), and 1 Hz (GPS position).

4.4 Data analysis

The data collected on the 35.5 km of the experiment for the 23 drivers were analysed to understand the conditions in which control transitions occurred most often. This study focuses on control transitions in cases that did not involve lane changes (within a time window of 10 seconds before and 10 seconds after the transition). The data were reduced to 1 Hz resolution, resulting in 31,165 observations.

Overall, the ACC system was Active in 83.8% of the observations, Active and accelerate in 3.4%, and Inactive in 12.8%. A leader was detected by the radar (120 m range) in 89.6% of the observations. This study analyses 23,568 1-s observations in which the ACC system is Active and a leader is detected. Among these, the number of observations for each driver ranges from 334 to 1936 (M=1025, SD=467). 55 observations (0.23%) were immediately followed by a DIDC transition to Inactive (deactivations), 106 (0.45%) by a DIDC transition to Active and accelerate (overruling), and 23,407 (99.3%) by no transitions. Transitions initiated by the system are not analysed. Drivers transferred to Inactive from 0 to 7 times (M=2.39, SD=1.83), and to Active and accelerate from 0 to 26 times (M=4.61, SD=5.88).

To explore the circumstances in which the control transitions were initiated, Figure 4.3 compares the empirical cumulative distribution functions of the driver behaviour characteristics when no transitions occurred, when the system was deactivated and when it was overruled. Table 4.1 presents the mean and the standard deviations of these variables and Table 4.2 the results of two-sample Kolmogorov-Smirnov tests on the similarity of the distributions among the three groups. Figure 4.3 *a* shows that most transitions were initiated few seconds after the ACC had been activated. Notably, 48.1% of the transitions to Active and accelerate occurred up to 7 seconds after the activation. The distributions of time after last activation differed significantly between the three groups.

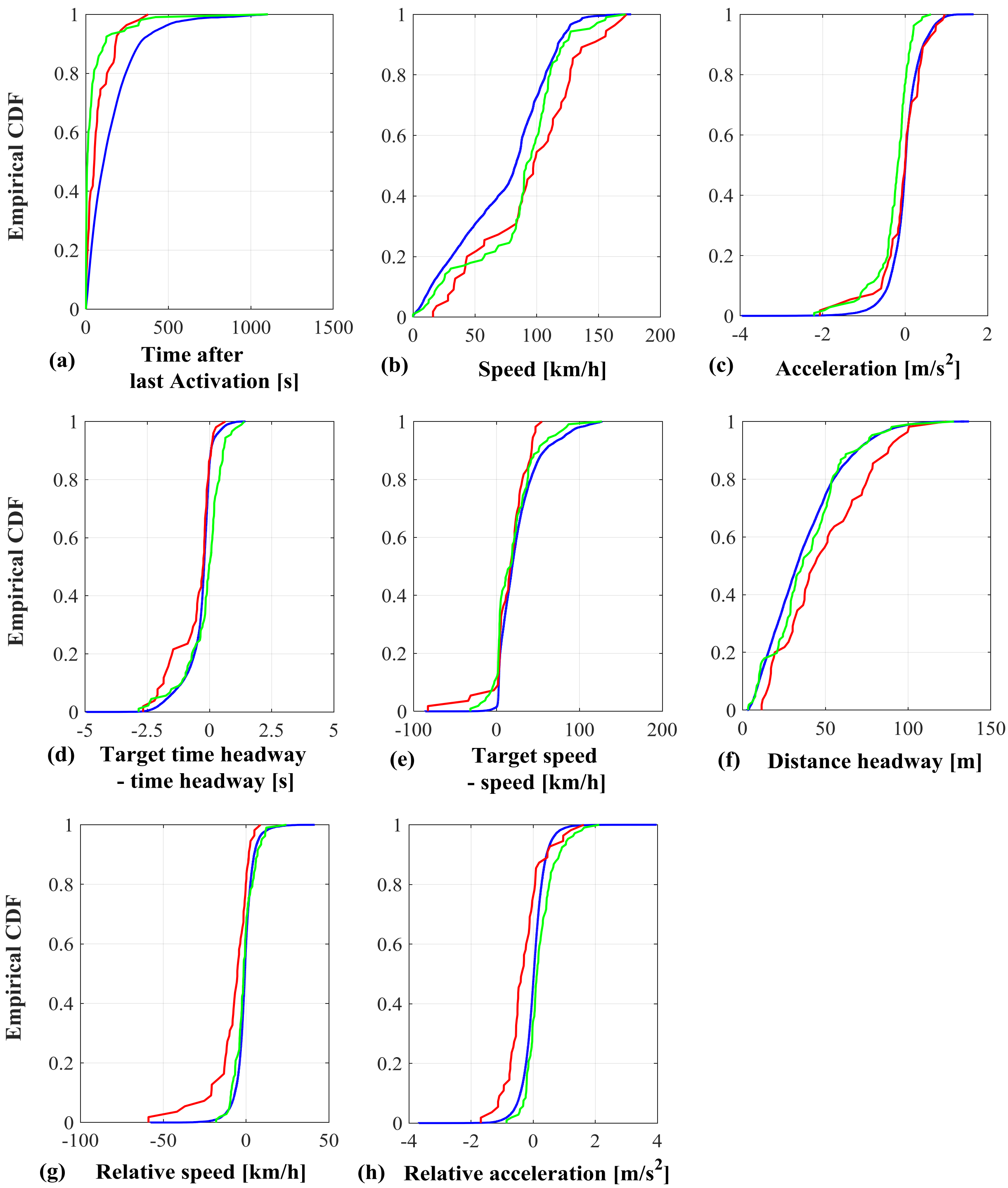


Figure 4.3: Empirical cumulative distribution functions of the driver behaviour characteristics when the system is maintained Active (blue), and when transitions to Inactive (red) and to Active and accelerate (green) are initiated. The variables plotted are listed as follows: (a) time after last activation, (b) speed, (c) acceleration, (d) target time headway – time headway, (e) target speed – speed, (f) distance headway, (g) relative speed, and (h) relative acceleration.

Figure 4.3 *b* indicates that most transitions were initiated at speeds between 80 and 130 km/h and, within this interval, transitions to Active and accelerate were more frequent at higher speeds. The distributions of speed differed significantly between the three groups. Figure 4.3 *c* shows that 76.1% of the transitions to Active and accelerate occurred when the vehicle decelerated. Figure 4.3 *d* illustrates that 86.3% of the deactivations occurred when the actual time headway was larger than that one set in the ACC. Figure 4.3 *e* shows that 7.3% of the deactivations and 11.3% of the overruling actions occurred when the speed was higher than the target speed set in the ACC. Figure 4.3 *f* suggests that, on average, deactivations were associated with larger distance headways. Figure 4.3 *g* shows that 80.0% of the deactivations and 65.1 % of the overruling actions occurred when the speed of the subject vehicle was higher than the speed of the leader. The distributions of relative speed differed significantly between transitions to Inactive and the other two groups. Figure 4.3 *h* indicates that 76.4% of the deactivations happened when the subject vehicle accelerated more than the leader. The distributions of relative acceleration differed significantly between the three groups. In addition, cut-in manoeuvres were detected comparing the distance headway from radar to the distance headway calculated using the speed and the acceleration of the subject vehicle and the leader in the previous observation. When this difference was larger than 7 m, it was assumed that the distance headway reduction was caused by a new vehicle cutting in. The main conclusion is that the driver behaviour characteristics of the subject vehicle and of the leader may influence significantly the choice to resume manual control.

Table 4.1: Mean and standard deviation of the driver behaviour characteristics when the system is maintained Active (A) and when control transitions are initiated to Inactive (I) and to Active and accelerate (AAc)

Variables	Description	A	I	AAc
Time after last activation	Time after the ACC has been activated in s	152 (155)	76.0 (83.2)	50.3 (128)
Speed	Speed of the subject vehicle in km/h	72.8 (37.9)	94.8 (40.9)	86.5 (36.9)
Acceleration	Acceleration of the subject vehicle in m/s^2	-0.00254 (0.390)	-0.0491 (0.549)	-0.272 (0.462)
Target time headway – time headway	Difference between the ACC target time headway and the time headway (front bumper to rear bumper) in s	-0.364 (0.561)	-0.574 (0.758)	-0.160 (0.780)
Target speed – speed	Difference between the ACC target speed set and the subject vehicle speed in km/h	25.6 (25.0)	16.2 (22.2)	20.2 (24.9)
Distance headway	Distance headway (front bumper to rear bumper) in m	36.7 (22.9)	49.8 (27.5)	39.1 (23.1)
Relative speed	Difference between the leader speed and the subject vehicle speed in km/h	-0.810 (5.72)	-7.84 (11.8)	-1.04 (6.33)
Relative acceleration	Difference between the leader acceleration and the subject vehicle acceleration in m/s^2	0.0142 (0.376)	-0.287 (0.609)	0.225 (0.479)

Table 4.2: Two-sample Kolmogorov-Smirnov Test (p-value) of the driver behaviour characteristics when the system is maintained Active (A) and when control transitions are initiated to Inactive (I) and to Active and accelerate (AAc)

Variables	A versus I	A versus AAc	I versus AAc
Time after last activation	$4.73 \cdot 10^{-5}$	$9.04 \cdot 10^{-27}$	$8.64 \cdot 10^{-5}$
Speed	0.00112	$4.91 \cdot 10^{-5}$	0.0486
Acceleration	0.432 (*)	$2.01 \cdot 10^{-10}$	0.00320
Target time headway – time headway	0.192 (*)	$1.79 \cdot 10^{-11}$	0.000110
Target speed – speed	0.239 (*)	0.00655	0.464(*)
Distance headway	0.00935	0.147(*)	0.0335
Relative speed	$2.86 \cdot 10^{-8}$	0.0902(*)	0.000230
Relative acceleration	$1.20 \cdot 10^{-8}$	0.00113	$7.67 \cdot 10^{-9}$

NOTE: (*) p-value>0.05.

Freeway sections of increased lane changing, merging and weaving were associated with more frequent control transitions. The number and percentage of observations in each road section are shown in Table 4.3. Deactivations occurred more often when drivers were on the freeway mainline close to an on-ramp and in the segment between the first exit sign and the exit (1600 m). Drivers overruled the system more often in proximity to on-ramps and between ramps placed at a distance shorter than 600 m, which might cause disturbances to traffic flow (FGSV, 2008).

Table 4.3: Number and percentage of observations in each road section when the system is maintained Active (A) and when control transitions are initiated to Inactive (I) and to Active and accelerate (AAc)

Variables	Description	A	I	AAc
On-ramps	Freeway mainline close to an on-ramp	3608 (15.4%)	16 (29.1%)	26 (24.5%)
Off-ramps	Freeway mainline close to an off-ramp	274 (1.2%)	3 (5.5%)	1 (0.9%)
Between ramps	Freeway mainline between ramps closer than 600 m	987 (4.2%)	3 (5.5%)	10 (9.4%)
Exits	Freeway mainline between the first exit sing and the exit (1600 m)	1934 (8.3%)	11 (20.0%)	3 (2.8%)
Total		23407 (100%)	55 (100%)	106 (100%)

Significant differences in transferring control were also associated with drivers with different characteristics. Table 4.4 presents the number and percentage of observations for each group of drivers and Table 4.5 the results of the chi-square test of independence between driver characteristics and the number of observations in each ACC system state. Females and drivers with 13 to 33 years of driving experience (31 to 50 years old) overruled the system less often. Drivers inexperienced with ADAS transferred control less often and drivers medium experienced with ADAS resumed control more often.

Table 4.4: Number and percentage of observations in each group based on the driver characteristic when the system is maintained Active (A) and when control transitions are initiated to Inactive (I) and to Active and accelerate (AAc)

Variables	A	I	AAc
Gender			
Males (n=15)	15707 (67.1%)	36 (65.5%)	86 (81.1%)
Females (n=8)	7700 (32.9%)	19 (34.5%)	20 (18.9%)
Driving Experience			
3-12 years (n=16)	16347 (71.6%)	38 (76.0%)	86 (88.7%)
13-33 years (n=7)	6493 (28.4%)	12 (24.0%)	11 (11.3%)
Experience with ADAS			
Inexperienced (n=6)	6246 (26.7%)	10 (18.2%)	15 (14.2 %)
Medium experienced (n=9)	7905 (33.8%)	22 (40.0%)	51 (48.1%)
Experienced (n=8)	9256 (39.5%)	23 (41.8%)	40 (37.7%)

Table 4.5: Chi-square test of independence between driver characteristic and number of observations in which the system is maintained Active (A) and control transitions are initiated to Inactive (I) and to Active and accelerate (AAc)

Variables	df	χ	p-value
Gender	2	9.49	0.009
Driving Experience	2	14.4	0.0007
Experience with ADAS	4	14.9	0.005

4.5 Choice model for transitions to manual control

A discrete choice model was developed for the decision to maintain the system Active, to transfer to Inactive (by pressing the brake pedal or the on-off button) or to Active and accelerate (by pressing the gas pedal). Since these transitions are intentionally initiated by the drivers, it was assumed that only one transition may occur within a 1-s interval, a value similar to the mean reaction time between the detection of a stimulus and the application of the response available in literature (Toledo et al., 2003). The choices are modelled for this time interval and are associated with the driver behaviour characteristics registered at the beginning of the interval. Repeated observations of multiple time intervals (panel data) are available for each driver. To predict the probabilities of transition choices capturing this panel dimension, a mixed logit model was estimated introducing a driver-specific error term ϑ_n assumed to be normally distributed over the sample (Toledo et al., 2003). This driver-specific error term captures unobserved preferences which affect all choices made by the individual driver over time (i.e., the alternative specific constants differ between drivers). The driver behaviour characteristics of the subject vehicle and of its direct leader, included as explanatory variables, capture state dependency (i.e., interdependencies between choice situations over time). Below, the final specification, selected based on statistical significance, is presented. The utility functions for remaining Active (A), transition to Inactive (I), and transition to Active and accelerate (AAc) for driver *n* at time *t* are given by equations (4.1)-(4.3):

$$U_n^A(t) = 0 + \varepsilon_n^A(t) \tag{4.1}$$

$$\begin{aligned} U_n^I(t) = {} & \alpha^I + \beta_{TimeAct}^I \cdot \log\big(TimeAct(t)\big) + \beta_{Speed} \cdot Speed(t) \\ & + \beta_{LowTarSpeed} \cdot LowTarSpeed(t) + \beta_{THW30}^I \cdot THW30(t) \\ & + \beta_{RelSpeed}^I \cdot RelSpeed(t) + \beta_{RelAcc}^I \cdot RelAcc(t) + \beta_{AntCutIn3}^I \cdot AntCutIn3(t) \\ & + \beta_{OnRamp} \cdot OnRamp(t) + \beta_{Exit}^I \cdot Exit(t) + \gamma \cdot \vartheta_n + \varepsilon_n^I(t) \end{aligned} \tag{4.2}$$

$$\begin{aligned} U_n^{AAc}(t) = {} & \alpha^{AAc} + \beta_{TimeAct}^{AAc} \cdot \log(TimeAct(t)) + \beta_{Speed} \cdot Speed(t) \\ & + \beta_{LowTarSpeed} \cdot LowTarSpeed(t) + \beta_{Acc-}^{AAc} \cdot AccNeg(t) + \beta_{Acc+}^{AAc} \cdot AccPos(t) \\ & + \beta_{RelSpeed}^{AAc} \cdot RelSpeed(t) + \beta_{CutIn}^{AAc} \cdot CutIn(t) + \beta_{OnRamp} \cdot OnRamp(t) \\ & + \beta_{Female}^{AAc} \cdot Female_n + \beta_{ExpDriv}^{AAc} \cdot ExpDriving_n + \gamma \cdot \vartheta_n + \varepsilon_n^{AAc}(t) \end{aligned} \tag{4.3}$$

where α^I and α^{AAc} are alternative specific constants, β^I and β^{AAc} are vectors of parameters associated with the explanatory variables listed in Table 4.7, γ is the parameter associated with the individual specific error term $\vartheta_n \sim N(0,1)$, and $\varepsilon_n^A(t)$, $\varepsilon_n^I(t)$ and $\varepsilon_n^{AAc}(t)$ are i.i.d. Gumbel – distributed error terms.

The model was estimated using the software PythonBiogeme (Bierlaire, 2016). The log likelihood values, the goodness of fit indicators are presented in Table 4.6 and the estimation results in Table 4.7. Most parameters associated with the explanatory variables in the utility functions are statistically significant at the 95% confidence level. The variables associated with transition-specific parameters had a significantly different impact on transitions to Inactive and to Active and accelerate. Both alternative specific constants are negative and large in magnitude, indicating that drivers are more likely to keep the system active than to transfer to manual control. Everything else being equal, drivers are more likely to overrule than to deactivate the system. The probability that drivers would resume manual control is highest in the first few seconds after the system has been activated. The logarithmic transformation is consistent with the empirical distribution function of time presented in Figure 4.3 *a* and resulted in a significant better fit than a linear specification. This effect is stronger for overruling than for deactivating the system. Analysing the driver behaviour characteristics of the subject vehicle, one notes that drivers are more likely to resume manual control at higher speeds. In addition, they are more likely to intervene when their speed is higher than the target speed set in the ACC and this probability increases for larger differences. Speeds lower than the target speed had non-significant effects on transitions. Drivers are more likely to overrule the system when the ACC acceleration is low. The time headway and the target time headway set in the ACC did not influence significantly the choice to overrule the system. Drivers are more likely to deactivate when the time headway is short for speeds higher than 30 km/h. The time headway at speeds lower than 30 km/h, the target time headway set in the ACC and the ACC acceleration did not have a significant effect on deactivations. Interestingly, the driver behaviour characteristics of the leader have a different effect on overruling and deactivating. Drivers are more likely to deactivate when they are faster (negative relative speed) and accelerate more (negative relative acceleration) than the leader and to overrule when they are slower (positive relative speed). Relative accelerations had a non-significant effect on choices to overrule. Drivers are more likely to deactivate the system when they expect that a vehicle will cut in during the next 3 s (proactive behaviour) and to overrule after a vehicle has cut in (reactive behaviour). This specification was selected based on statistical significance, assuming that drivers are able to anticipate traffic conditions up to 3 s downstream (without any error in their predictions) and can be influenced by events occurred in the previous 10 s.

Road locations influenced significantly the choices to transfer control. Drivers are more likely to deactivate the system close to on-ramps, between two ramps (closer than 600 m), and before exiting the freeway. The latter is consistent with previous findings (Pereira et al., 2015). Drivers are more likely to overrule close to on-ramps and between two ramps. Proximity to exits did not influence significantly the decision to overrule the system. Proximity to off-ramps had a non-significant effect on transitions.

Table 4.6: Statistics of the mixed logit model

Statistics	
Number of parameters K associated with explanatory variables	17
Number of alternative specific constants	2
Number of drivers	23
Number of observations	23,568
Constant log likelihood $L(c)$	-1067
Final log likelihood $L(\hat{\beta})$	-818
Adjusted likelihood ratio index (rho-bar-squared) $\bar{\rho}^2 = 1 - \frac{(L(\hat{\beta}) - K)}{L(c)}$	0.217

Table 4.7: Estimation results of the mixed logit model

Variable	Description	Parameters	Estimate	Robust t-stat.	Robust p-value
-	Alternative specific constant	α^{I}	-6.56	-13.3	<0.005
-	Alternative specific constant	α^{AAc}	-3.01	-6.19	<0.005
TimeAct	Time after the ACC has been activated in s	$\beta^{I}_{TimeAct}$	-0.198	-1.77	0.08
TimeAct	Time after the ACC has been activated in s	$\beta^{AAc}_{TimeAct}$	-0.740	-7.86	<0.005
Speed	Speed of the subject vehicle in km/h	β_{Speed}	0.00705	2.59	0.01
Low TarSpeed	Difference between the target speed set in the ACC and the speed of the subject vehicle when the former is relatively lower in km/h	$\beta_{TarSpeed-}$	-0.0290	-2.04	0.04
AccNeg	Acceleration of the subject vehicle in m/s^2 when this value is negative	β^{AAc}_{Acc-}	-1.52	-5.30	<0.005
AccPos	Acceleration of the subject vehicle in m/s^2 when this value is positive	β^{AAc}_{Acc+}	-3.71	-4.38	<0.005
THW30	Time headway (front bumper to rear bumper) in s when the speed is higher than 30 km/h	β^{I}_{THW30}	-0.357	-1.48	0.14
RelSpeed	Relative speed (i.e., leader speed – subject vehicle speed) in km/h	$\beta^{I}_{RelSpeed}$	-0.106	-9.52	<0.005
RelSpeed	Relative speed (i.e., leader speed – subject vehicle speed) in km/h	$\beta^{AAc}_{RelSpeed}$	0.0574	3.09	<0.005
RelAcc	Relative acceleration (i.e., leader acceleration – subject vehicle acceleration) in m/s^2	β^{I}_{RelAcc}	-1.40	-4.59	<0.005
AntCutIn3	Number of vehicles that will cut in in the following three seconds	$\beta^{I}_{AntCutIn3}$	1.77	6.14	<0.005
CutIn	Dummy variable equal to 1 when a vehicle cuts in in front of the subject	β^{AAc}_{CutIn}	1.91	3.23	<0.005
OnRamp	Dummy variable equal to 1 when the drivers are in the mainline close to an on-ramp, or between two ramps closer than 600 m (FGSV, 2008)	β_{OnRamp}	0.541	3.49	<0.005
Exit	Dummy variable equal to 1 when the distance to the closest exit is shorter than 1600 m (first exit sign)	β^{I}_{Exit}	1.93	4.94	<0.005
Female	Dummy variable denoting female drivers	β^{AAc}_{Female}	-0.985	-2.90	<0.005
ExpDriving	Years of driving experience	$\beta^{AAc}_{ExpDriv}$	-0.0456	-1.65	0.10
ϑ_n	Individual specific error term	γ	0.857	4.56	<0.005

Notably, driver characteristics have a significant effect on transition choices. Female drivers and experienced drivers are less likely to overrule the system. However, these driver characteristics did not influence significantly deactivations. In addition, experience with ADAS did not impact significantly the transition choices. The driver specific error terms for overruling and deactivating the ACC were assumed to be equal because they were strongly correlated (r = 0.908), suggesting that drivers who deactivate more frequently also overrule more frequently. The effects of these terms on the transitions were non-significantly different, meaning that the variability between drivers in deactivating and overruling is similar (i.e., the alternative specific constants have equal variance).

To illustrate the impact of changes in the explanatory variables on the choice probabilities, the choice probability ratio was calculated between a baseline observation and observations in which only one variable was changed while keeping all the other variables fixed. In the baseline observation (choice probability ratio equal to 1), the driver was assumed to be a male with 13 years of driving experience. The actual speed was assumed to be equal to 89.3 km/h and lower than the target speed, the acceleration -0.195 m/s^2, the time headway 1.79 s, the relative speed -3.37 km/h, and the relative acceleration 0.0648 m/s^2. In addition, it was assumed that the ACC system had been activated for 59 s and the observation was not influenced by ramps, exits or cut-in manoeuvres. These values were chosen based on the average conditions of the observed control transitions. The results are shown in Figure 4.4 (ratio variables) and Table 4.8 (ordinal and nominal variables). All results are consistent with previous discussions. Comparing the plots in Figure 4.4 reveals that the time after activation, the acceleration (negative), the difference between target speed and actual speed (negative) and the driver specific error term (positive) have a stronger impact on the decision of overruling the system. The difference between target speed and actual speed (negative), the relative speed (negative), the relative acceleration (negative) and the driver specific error term (positive) are the variables which influence most the decision of deactivating the system. In Table 4.8, the probability of deactivations is strongly influenced by the number of vehicles which are expected to cut in in the next three seconds. Finally, Appendix A presents the *in-sample-out-of-time* and *out-of-sample-in-time* validation analyses of the model estimated.

Table 4.8: Effect of the explanatory variables (ordinal and nominal) on choice probability ratio (probability predicted divided by probability baseline observation) of keeping ACC active (A), transferring to Inactive (I), and transferring to Active and accelerate (AAc)

Variables	A	I	AAc
CutIn	0.9909	0.9909	6.687
$AntCutIn_3$ = 1	0.9977	5.838	0.9977
$AntCutIn_3$ = 2	0.9846	33.71	0.9846
$AntCutIn_3$ = 3	0.9142	183.1	0.9142
OnRamp	0.9985	1.715	1.715
Exit	0.9972	6.884	0.9972
Female	1.001	1.001	0.3737

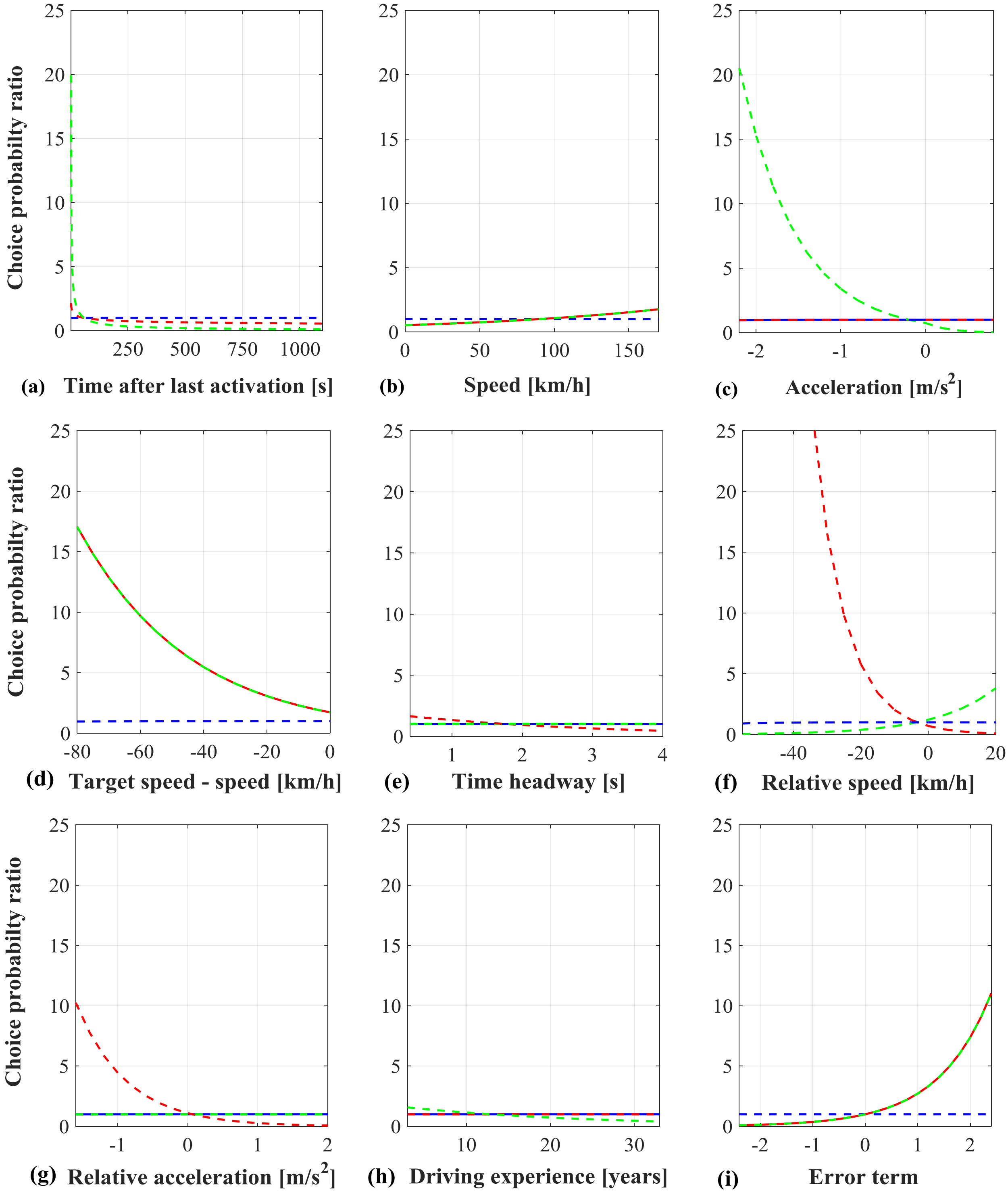


Figure 4.4: Effect of the explanatory variables and driver specific error term on choice probability ratio (probability predicted divided by probability baseline observation) of keeping ACC active (blue), transferring to Inactive (red), transferring to Active and accelerate (green). The variables plotted are listed as follows: (a) time after last activation, (b) speed, (c) acceleration, (d) target speed – speed, (e) time headway, (f) relative speed, (g) relative acceleration, (h) driving experience, and (i) driver specific error term γ.

4.6 Discussion and conclusions

This study identified the factors that influence drivers' decision to initiate a control transition between ACC and manual driving, which may have a significant impact on traffic flow efficiency (Varotto et al., 2015) and safety. To gain empirical insight into the decision-making process, a mixed logit model was estimated with panel data collected in an on-road study. The results in this model showed that drivers are more likely to deactivate the system when approaching a slower leader, when driving above the ACC target speed, and when expecting vehicles cutting in the following 3 s. Drivers are more likely to overrule the ACC by pressing the gas pedal a few seconds after the system has been activated, when the vehicle decelerates, and when driving above the ACC target speed.

This study concludes that drivers deactivate the system when the speed and acceleration of the leader are lower than their (unobservable) desired speed and acceleration. This condition happens when the leader is slower than the subject vehicle and the ACC system automatically decreases the speed to synchronize (similar to findings in Pereira et al. (2015) and in Xiong and Boyle (2012)). The desired speed and acceleration might be influenced by environmental conditions which cause disturbances to traffic flow such as proximity to ramps and exits. In addition, drivers deactivate to anticipate cut-ins in the following few seconds, questioning whether the system will be able to handle a potential safety-critical situation. Drivers press the gas pedal when the ACC acceleration is lower than their desired acceleration, which is influenced by the functioning of the system (e.g., how long the system has been active) and by environmental conditions (e.g., proximity to ramps). In general, drivers transfer to manual control more often when driving above the ACC target speed (which has been reached by pressing the gas pedal in the previous observations), meaning that the target speed does not correspond to the desired speed anymore. Notably, some drivers (positive driver specific error term) are more likely to deactivate and to overrule the system than others. Further research is needed to determine the origin of this effect, which may be linked to personality traits and driving styles.

The generalizability of the results presented is subject to certain limitations. For instance, the participants were not a sample representative of the driver population in terms of age, gender, employment status and experience with ADAS. Being limited to 23 participants who drove the test route only once, this study gained little insight into the factors explaining heterogeneity between drivers. Moreover, the results presented are related to the characteristics of the ACC system tested and cannot be directly generalized to other technologies. Finally, the effect of the average traffic conditions (mean speed and flow from point-based loop detectors) and of the variable speed limits were not accounted for in the choice model, assuming that data at the individual vehicle level (driver behaviour characteristics of the subject vehicle and of the direct leader) are more informative predictors of the decision-making process.

The key implication of this study is that, to assess the effects of ACC on traffic flow including control transitions, a conceptual framework is needed that links ACC system settings, driver behaviour characteristics, driver characteristics and environmental factors. Future research will focus on the mathematical formulation of this novel framework and on the model calibration using the dataset available. The final model can be implemented into a microscopic simulation to assess the effects on control transitions on traffic flow.

Chapter 5

Modelling decisions of control transitions and target speed regulations in full-range Adaptive Cruise Control based on Risk Allostasis Theory

Few studies have estimated the probability that drivers resume manual control in ACC based on empirical data. Results in Chapter 4 have shown that drivers are likely to deactivate full-range ACC when approaching a slower leader and to overrule it by pressing the gas pedal a few seconds after the system has been activated (DIDC transitions). Notwithstanding the influence of these control transitions on driver behaviour, a theoretical framework explaining drivers' decisions to transfer control and to regulate the target speed in full-range ACC is currently missing.

This chapter develops a modelling framework describing the underlying decision-making process of drivers with full-range ACC at an operational level, grounded on Risk Allostasis Theory (RAT). The chapter is structured as follows. Section 5.1 introduces models of control transitions in ACC. Section 5.2 reviews driver control theories and driver behaviour models that are suitable to explain driver interaction with ACC. Section 5.3 describes the mathematical formulation of the modelling framework. Drivers choose to resume manual control or to regulate the ACC target speed (binary logit and regression models) if the perceived level of risk feeling and task difficulty falls outside the range considered acceptable to maintain the system active (generalized ordered probit model with random thresholds). The model was estimated using full-information maximum likelihood methods as described in Section 5.4. Section 5.5 presents the case study, including an overview of the controlled on-road experiment (for a detailed description, refer to Chapter 3), the data analysis, the estimation results, and validation analyses of the model. Section 5.6 discusses the main contributions of the proposed modelling framework. Section 5.7 summarizes the main factors influencing the decision making of drivers with ACC, and directions for future research.

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NOTE: The original paper was subject to minor textual revision.

5.1 Introduction

Automated vehicles are expected to mitigate traffic congestion and accidents (European Commission, 2017). Automated vehicles may have a beneficial impact on road capacity, traffic flow stability, and queue discharge rates (Hoogendoorn et al., 2014). The first step towards predicting these impacts is to investigate currently available systems such as Adaptive Cruise Control (ACC). ACC assists drivers in maintaining a target speed and time headway and therefore has a direct adaptation effect on the longitudinal control task (Martens and Jenssen, 2012). The influence of ACC systems on driver behaviour has been investigated, mainly via driving simulator studies, since the 1990s. On-road experiments (Alkim et al., 2007; Malta et al., 2012; NHTSA, 2005; Schakel et al., 2017) have shown that ACC systems influence substantially driver behaviour. When the ACC is active, drivers keep larger time headways (Alkim et al., 2007; Malta et al., 2012; NHTSA, 2005; Schakel et al., 2017), and change lane in advance to anticipate possible interactions with slower vehicles (Alkim et al., 2007). These results, however, might be influenced by the conditions in which the ACC system is activated, such as light-medium traffic, medium-high speeds, and non-critical traffic situations.

In certain traffic conditions, drivers might prefer to disengage the system and resume manual control, or the system disengages because of its operational limitations. These control transitions (Lu et al., 2016) between automated and manual driving may influence traffic flow efficiency (Varotto et al., 2015) and safety (Vlakveld et al., 2015). Lu et al. (2016) classified control transitions based on who (automation or driver) initiates the transition and who is in control afterwards: ‘Driver Initiates transition, and Driver in Control after’ (DIDC), ‘Driver Initiates transition, and Automation in Control after’ (DIAC), and ‘Automation Initiates transition, and Driver in Control after’ (AIDC). The situations in which these transitions happen are influenced by the characteristics of the driving assistance system, the drivers themselves, the road, and the traffic flow (Varotto et al., 2014). Field Operational Tests (FOTs) have suggested that drivers initiate DIDC transitions with ACC systems that do not operate at speeds lower than 30 km/h to avoid potentially safety-critical situations (Xiong and Boyle, 2012), to keep a stable speed in medium–dense traffic conditions (Viti et al., 2008), to adapt the speed before changing lane, to create or reduce a gap when other vehicles merge into the lane, and to avoid passing illegally a slower vehicle on the left lane (Pauwelussen and Feenstra, 2010). Recently, ACC systems operating also at low speeds in stop-and-go traffic conditions (*full-range* ACC), therefore overcoming the functional limitations of earlier versions, have been introduced into the market. These ACC systems might be activated and deactivated in different situations, and are more likely to be active in dense traffic conditions. A controlled on-road experiment showed that drivers using full-range ACC initiate DIDC transitions when exiting the freeway, when approaching a moving vehicle, when changing lane, and when a vehicle cuts in or the leader changes lane (Pereira et al., 2015).

ACC might have a positive impact on traffic flow efficiency when it is active in dense traffic (Van Driel and Van Arem, 2010). To evaluate this impact, mathematical models of automated and manually driven vehicles can be implemented into microscopic traffic simulation models. However, most car-following and lane-changing models currently used to evaluate the impact of ACC do not describe control transitions. A few microscopic traffic simulation models (Klunder et al., 2009; Van Arem et al., 1997; Xiao et al., 2017) have proposed deterministic decision rules for transferring control, disregarding inconsistencies in the decision-making process, heterogeneity between and within drivers, and dependencies between different levels of decision making (for a review, see Varotto et al. (2017)). Thus, the traffic flow predictions based on these models could be unreliable.

To improve the realism of current traffic flow models, insights from driver psychology and human factors should be incorporated (Hamdar et al., 2015; Saifuzzaman and Zheng, 2014). To date, few studies have proposed a conceptual model framework explaining control transitions based on theories of driver behaviour and have estimated the probability that drivers transfer control based on empirical data. Using a mixed logit model, Xiong and Boyle (2012) predicted the likelihood that drivers would brake resuming manual control while they were closing in on a leader. Recently, the main factors influencing drivers' choice to initiate a DIDC transitions with full-range ACC were identified based on driver behaviour data in a wider range of situations that did not involve lane changes (Varotto et al., 2017). Drivers have higher probabilities to deactivate the ACC when closing in on a slower leader, when supposing vehicles cutting in, and before exiting the freeway. Drivers have higher probabilities to overrule the ACC system by pressing the gas pedal when the vehicle decelerates and a few seconds after the activation of the system. Interestingly, some drivers have higher probabilities to resume manual control than others. However, this study did not capture explicitly the unobservable constructs that inform driver decisions and ignored the possibility of adapting the ACC system settings (speed and time headway) to regulate the longitudinal control task.

This study develops such a mathematical framework to model driver decisions to resume manual control and to regulate the target speed in full-range ACC. The model is based on the Risk Allostasis Theory (RAT) (Fuller, 2011), captures explicitly interdependencies between the two decisions, and can be fully estimated based on driver behaviour data.

5.2 Literature review

The literature review focuses on studies proposing conceptual and mathematical models of driver behaviour that are suitable to explain control transitions and target speed regulations in ACC. Section 5.2.1 introduces driver control theories and Section 5.2.2 conceptual models explaining adaptations in driver behaviour. Section 5.2.3 discusses a model framework that has the potential to capture interdependencies between different driver behaviours. Section 5.2.4 summarizes the research gaps and formulates the research objectives.

5.2.1 Driver control theories

The driving task can be divided into three levels: strategical (planning), tactical (manoeuvring), and operational (control) (Michon, 1985). The strategical level represents the planning phase of the trip, for instance in terms of mode and route choice. The tactical level includes decisions on manoeuvres such as overtaking and gap acceptance. The operational level defines the direct longitudinal and lateral control of the vehicle. This level has been studied in driver control theories (for a review, refer to Ranney (1994), Rothengatter (2002) and Fuller (2011)). Several theories have been developed to explain the underlying motivational and cognitive aspects of driver control, such as the Risk Homeostasis Theory (Wilde, 1982), the Zero-risk Theory (Näätänen and Summala, 1974; Summala, 1988), the Task-Capability-Interface (TCI) model (Fuller, 2000, 2005), the Monitor Model (Vaa, 2007), and the Safety Margin Model (Summala, 2007). These models differ in terms of the reference criteria in the control system (e.g., risk of collision, task difficulty, emotions, driving comfort). However, these different reference criteria may reflect a hidden consensus (Fuller, 2011): the most important motives influencing drivers' decisions may be classified under task demand elements, while motives such as driving comfort can be considered secondary to those relating to safety.

Fuller (2011) proposed the Risk Allostasis Theory (RAT), which assimilated the most recent competing theories (Summala, 2007; Vaa, 2007) into the TCI model (Fuller, 2000, 2005). The RAT argues that driver control actions are primarily informed by the desire to maintain the feeling of risk and task difficulty within an acceptable range, which varies over time. Drivers perceive risk feelings in the same way as they experience task difficulty (Fuller et al., 2008). The maximum value of task difficulty acceptable is associated with fear of losing control and the minimum value of task difficulty acceptable is associated with frustration determined by low driving performances (Fuller, 2011). The perceived task difficulty is related to the difference between perceived task demand and perceived driver capability (Fuller, 2000, 2005).

The perceived task demand is influenced by the presence and behaviour (both actual and anticipated) of other road users, by the road environment (e.g., road surface and visibility), and by the characteristics of the vehicle (e.g., interface and vehicle performance) (Fuller, 2002; Fuller and Santos, 2002). The perceived driver capability is determined by driver characteristics, such as driving experience and age, and by human factors, such as distraction, emotions, stress and fatigue (Fuller, 2002; Fuller and Santos, 2002). The perceived driver capability is ultimately expressed in driver behaviour characteristics, such as the chosen speed and distance headway (Fuller, 2011). When the perceived capability is stable, variations in the perceived task demand directly influence the feeling of risk and task difficulty. Empirical findings have shown that the feeling of risk and task difficulty increase when the speed increases (Fuller et al., 2008; Lewis-Evans and Rothengatter, 2009) and when the time headway decreases (Lewis-Evans et al., 2010). At speeds higher than the most comfortable speed for the driver, the perceived feeling of risk and task difficulty are correlated to estimates of statistical risk (Fuller et al., 2008). The latter can be expressed by measurable variables such as time to collision or time to line crossing. At lower speeds, however, the perceived feeling of risk is not correlated to estimates of statistical risk (Fuller et al., 2008). This is one of the key differences from previous driver control theories based on estimates of statistical risk (Wilde, 1982). It is still subject of debate in the field of driver psychology whether drivers can perceive changes in risk feelings in low risk situations and are informed by these changes in their behaviours (Fuller, 2011; Lewis-Evans et al., 2010; Lewis-Evans and Rothengatter, 2009).

The acceptable level of risk feeling and task difficulty can be influenced by driver characteristics (gender, experience, age and personality) and factors that vary over time for each individual driver (e.g., journey goals and emotional state) (Fuller, 2011). This variation of the risk thresholds over time is one of the key features that distinguish the Risk Allostasis Theory from previous theories based on risk homeostasis. Drivers decrease their speed when the risk feeling and task difficulty are higher than the maximum value acceptable and increase the speed when they are lower than the minimum value acceptable. However, they might be constrained in their decisions by performance limitations of the vehicle, congested traffic, and compliance to speed limits. These findings from driver psychology should be included into a conceptual model framework to explain driver behaviour with driving assistance systems such as the ACC.

5.2.2 Conceptual models for adaptations in driver behaviour

In driver psychology, adaptations are defined as the behavioural aspects that can be observed after a change in road traffic (Martens and Jenssen, 2012). Few studies have proposed conceptual models of adaptations in driver behaviour based on the control theories described in the previous section. The usage of ACC, which maintains a target speed and time headway, has a direct impact on the longitudinal control task of drivers. Xiong and Boyle (2012) proposed a conceptual model of drivers' adaptation to ACC which includes initiating factors (actual risk) and mediating factors (perceived risk). In this model, the actual risk is determined by the distance headway, environmental conditions (weather, road type, lighting conditions, traffic density) and the response of the system, while the perceived risk is influenced by the ACC system settings (speed and time headway), the driver characteristics, experience with and attitudes towards the system. This model is applied to predict driver decision making (i.e., manually brake or not) when approaching a slower leader.

Similarly, driver control theories have been used to explain adaptation effects in longitudinal driving behaviour. Hoogendoorn et al. (2013) and Saifuzzaman et al. (2015) incorporated the Task-Capability-Interface (TCI) model proposed by Fuller (2005) into car-following models to capture compensation effects due to driver distraction. Hoogendoorn et al. (2013) assumed that the maximum acceleration, the maximum deceleration, the free speed and the desired time headway are dependent on the task difficulty, expressed as difference between task demand and driver capability. However, the task difficulty was not explicitly linked to measurable driver behaviour characteristics and driver characteristics. Saifuzzaman et al. (2015) defined the task difficulty as the ratio of task demand and driver capability. The task demand increases when the speed of the subject vehicle increases and when the distance headway decreases. The driver capability is inversely proportional to the desired time headway (unobservable) and the sensitivity towards the task difficulty level is captured by a specific parameter. Human factors are captured by a component of the reaction time and a parameter representing the perceived risk. The task difficulty function was used to modify the desired acceleration in existing car-following models. These advanced car-following models were applied to predict driver behaviour in regular driving conditions and under distraction due to phone usage.

These studies show that driver control theories can be incorporated into existing models of driver behaviour to capture adaptations. The feeling of risk and task difficulty can be expressed as a function of driver behaviour characteristics such as speed and distance headway. A conceptual model framework similar to that one proposed by Xiong and Boyle (2012) can be developed to explain different driver behaviours with ACC (control transitions and target speed regulations) in a wide range of traffic situations.

5.2.3 Integrated driver behaviour models

Few driver behaviour models (e.g., car-following and lane changing models) have captured the interdependencies between different driving behaviours and explained these behaviours based on underlying constructs that motivate drivers' decisions. For these purposes, previous studies have proposed modelling frameworks based on discrete choice models, which are flexible from a behavioural perspective, provide statistical techniques to capture complex error structures and facilitate a rigorous estimation of the model parameters (Choudhury, 2007; Danaf et al., 2015; Farah and Toledo, 2010; Koutsopoulos and Farah, 2012; Toledo, 2003). In addition, these models are suitable for implementation into a microscopic traffic flow simulation because each individual is modelled independently. Toledo (2003) developed an integrated driving behaviour model predicting both acceleration (regression models) and lane changes (discrete choice models) based on drivers' unobservable short-term goals and plans. This model structure accommodates changes in both discrete and continuous variables, capturing interdependencies across driving decisions in terms of causality, unobserved driver and vehicle characteristics, and state dependency (Toledo et al., 2007; Toledo et al., 2009). The parameters of all model components were estimated simultaneously using maximum likelihood methods (Toledo et al., 2009). This review concludes that an integrated driver behaviour model can be developed to model mathematically driver decisions to transfer control and regulate the target speed in full-range ACC capturing unobservable constructs such as feeling of risk and task difficulty.

5.2.4 Research gaps and objectives

Few studies have proposed conceptual model frameworks based on insights from driver psychology to explain drivers' choices to resume manual control in ACC. The model framework proposed by Xiong and Boyle (2012) is limited to situations in which the subject vehicle approaches a slower leader. A comprehensive conceptual framework for driver behaviour at an operational level with ACC and a flexible mathematical formulation for this modelling framework are currently missing. Previous studies ignored the possibility of adapting the ACC system settings (time headway and speed) to regulate the longitudinal control task. Drivers can decrease their actual speed by braking or by decreasing the ACC target speed and can increase their actual speed by pressing the gas pedal or by increasing the target speed. To model decisions that are naturally linked such as control transitions and target speed regulations and to explain these decisions based on current theories of driver behaviour, a flexible modelling framework is needed capturing unobservable constructs and interdependencies between discrete and continuous variables. The main objectives of the current study are as follows:

(1) to develop a conceptual model framework that explains driver decisions to resume manual control and to regulate the target speed grounded on the Risk Allostasis Theory (Fuller, 2011);

(2) to develop a mathematical formulation for this modelling framework based on the integrated driver behaviour models (Toledo, 2003), which describes underlying constructs, captures interdependencies between different decisions, and can be fully estimated using driver behaviour data.

5.3 Modelling framework for driver decisions to resume manual control and to regulate the target speed in full-range ACC

The conceptual modelling framework assumes that feeling of risk and task difficulty (Fuller, 2011) are the main factors that inform drivers' decisions with full-range ACC at an operational level. This hypothesis is supported by empirical findings in Varotto et al. (2017). Drivers will choose to decrease (or increase) their actual speed if the perceived level of risk feeling and task difficulty (RFTD) is higher (or lower) than the maximum (or minimum) value which is considered acceptable to maintain the ACC active and the current ACC target speed. The actual speed can be regulated by adapting the ACC target speed or by resuming manual control.

Figure 5.1 presents the model framework. Two levels of decision making describing both transitions to manual control (discrete choice) and target speed regulations (continuous choice) with ACC are proposed: risk feeling and task difficulty evaluation, and ACC system state and ACC target speed regulation choice. The decision-making process is latent (unobservable). Driver actions to resume manual control and to regulate the target speed are observed, while the perceived level of RFTD is latent. At the highest level, the driver evaluates whether the perceived level of RFTD falls within the range which is considered acceptable to maintain the ACC active and the current ACC target speed. The perceived RFTD is influenced by the driver behaviour characteristics of the subject vehicle and of the leader. The acceptable range with the ACC active varies between drivers and within drivers over time, being influenced by driver characteristics, by the functioning of the system, and by the environment. If the perceived RFTD level is higher than the maximum value acceptable, the driver will choose to deactivate the system or to decrease the ACC target speed maintaining the system active. If the perceived RFTD level is lower than the minimum value acceptable, the driver will choose to overrule the ACC by pressing the gas pedal, to increase the ACC target speed maintaining the system active, or not to intervene. The latter is introduced to capture drivers' difficulties to perceive changes in feeling of risk and task difficulty in low risk situations, which might be influenced by human factors (unobservable) such as errors, shifts in attention and distraction (Fuller and Santos, 2002). These decisions are influenced by the driver behaviour characteristics, by the functioning of the system, by environmental conditions, and by driver characteristics.

The model framework allows capturing directly drivers' propensity to maintain the ACC system active and interdependencies among decisions to transfer control and to regulate the target speed through appropriate model specifications at the different levels of decision making. This is further explained in Section 5.4, which presents the mathematical formulation of the model based on this conceptual structure.

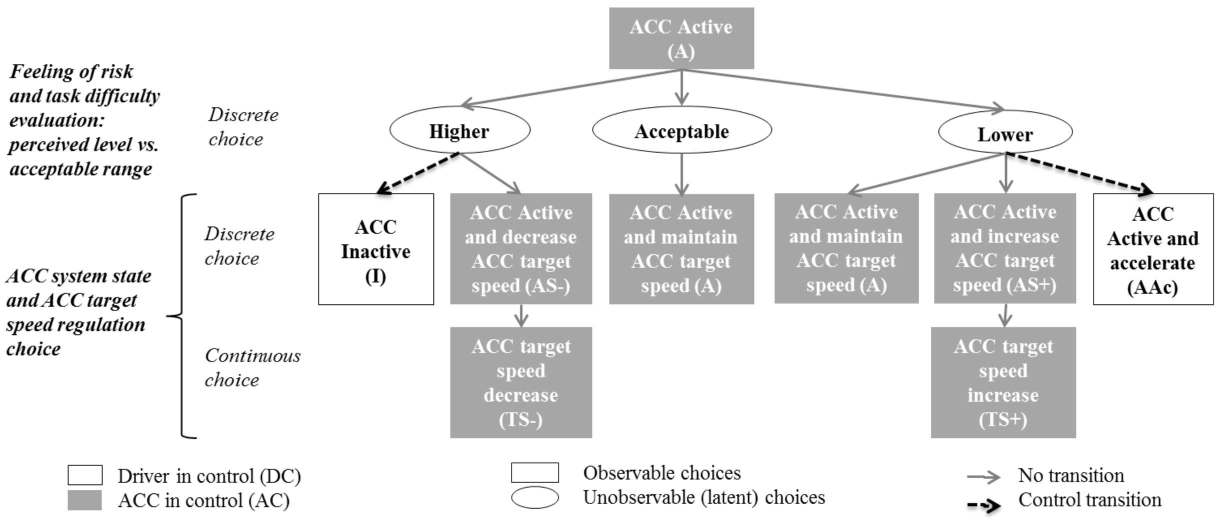

Figure 5.1: Conceptual model for driver decisions to resume manual control and to regulate the target speed in full-range ACC.

5.4 Mathematical formulation of the model for driver decisions to resume manual control and to regulate the target speed in full-range ACC

To implement the conceptual model presented in Section 5.3, a flexible mathematical framework is needed which is able to capture unobservable constructs and interdependencies between different decisions made by the same driver. Modelling frameworks based on choice models satisfy these requirements. In this study, choice models are preferred to alternative methods (e.g., artificial intelligence) because the model structure can be selected based on insights from driver control theories and the estimation results are directly interpretable.

In this mathematical framework, the magnitude of the ACC target speed regulation is chosen simultaneously to the system state and correlations between these two choices are captured explicitly. In addition, interdependencies across decisions are addressed in terms of causality, unobserved driver characteristics, and state dependency (Toledo, 2003). Causality is addressed by modelling the decisions taken at the lower levels as conditional on the decisions taken at the higher levels. This two-level model structure allows capturing explicitly drivers' propensity to not intervene when the ACC system is active. Unobserved driver characteristics are modelled by introducing driver-specific error terms in each level of decision making. State dependency (i.e., interdependencies between choice situations over time) is addressed by including the driver behaviour characteristics of the subject vehicle and of its direct leader as explanatory variables in the different levels. The model formulation is presented in Sections 5.4.1-5.4.3.

5.4.1 Level 1: risk feeling and task difficulty evaluation (discrete choice)

The risk feeling and task difficulty evaluation (RFTDE) model is formulated as a generalized ordered probit model with random thresholds (Castro et al., 2013; Eluru et al., 2008; Greene and Hensher, 2009, 2010). This model formulation represents the ordinal and discrete nature of the risk feeling and task difficulty evaluation (risk lower than acceptable, acceptable risk, and risk higher than acceptable), capturing both observed and unobserved heterogeneity in the minimum and in the maximum risk acceptable. This ordinal response structure is based on the assumption that an unobservable risk feeling and task difficulty (RFTD) determines the observable decisions of drivers. The RFTD is modelled as a latent variable that follows a normal distribution. Driver *n* chooses at time *t* whether the perceived RFTD is lower than the minimum risk acceptable (L), falls within the acceptable risk range (Ac) or is higher than the maximum risk acceptable (H) as presented in equation (5.1):

$$\mathrm{RFTDE_n(t)} = \begin{cases} \mathrm{L}, & \mathrm{RFTD_n(t)} < \mathrm{MinAc_n(t)} \\ \mathrm{Ac}, & \mathrm{MinAc_n(t)} < \mathrm{RFTD_n(t)} < \mathrm{MaxAc_n(t)} \\ \mathrm{H}, & \mathrm{RFTD_n(t)} > \mathrm{MaxAc_n(t)} \end{cases} \tag{5.1}$$

where $\mathrm{RFTDE_n(t)}$ is the choice indicator, and $\mathrm{MinAc_n(t)}$ and $\mathrm{MaxAc_n(t)}$ are the variables that represent the minimum and the maximum acceptable risk for each driver at time *t*. The non-linear formulation of the minimum and of the maximum risk acceptable allows to distinguish mathematically the thresholds from the latent regression, guarantees that both thresholds are positive, and preserves the ordering of the thresholds ($-\infty < \mathrm{MinAc_n(t)} < \mathrm{MaxAc_n(t)} < \infty$) (Greene and Hensher, 2009, 2010). The lowest and the highest acceptable risk are functions of explanatory variables as shown in equations (5.2)-(5.3):

$$\mathrm{MinAc}_n(t) = \exp\left(\mu^L + \boldsymbol{\tau}^{\mathbf{L}} \cdot \mathbf{X}_{\mathbf{n}}^{\mathbf{L}}(\mathbf{t}) + \gamma^L \cdot \vartheta_n\right) \tag{5.2}$$

$$\mathrm{MaxAc}_n(t) = \mathrm{MinAc}_n(t) + \exp\left(\mu^H + \boldsymbol{\tau}^{\mathbf{H}} \cdot \mathbf{X}_{\mathbf{n}}^{\mathbf{H}}(\mathbf{t}) + \gamma^H \cdot \vartheta_n\right) \tag{5.3}$$

where μ^L and μ^H are the constants, $\boldsymbol{\tau}^{\mathbf{L}}$ and $\boldsymbol{\tau}^{\mathbf{H}}$ are vectors of parameters associated with the explanatory variables $\mathbf{X}_{\mathbf{n}}^{\mathbf{L}}(\mathbf{t})$ and $\mathbf{X}_{\mathbf{n}}^{\mathbf{H}}(\mathbf{t})$, γ^L and γ^H are the parameters associated with the individual specific error term $\vartheta_n \sim N(0,1)$. The thresholds vary within individuals over time due to observed variables and between individuals due to observed variables and unobserved heterogeneity. Relevant explanatory variables that can be included into the threshold equations are driver characteristics, variables related to the functioning of the ACC system, and characteristics of the freeway segment. The driver-specific error term ϑ_n captures unobserved preferences that influence all choices taken by the individual over time. This error term varies between drivers but it is constant between choice situations for the same driver. The mean risk feeling and task difficulty perceived by drivers is a function of explanatory variables as described in equation (5.4):

$$\mathrm{RFTD}_n(t) = \omega + \boldsymbol{\lambda} \cdot \mathbf{X}_{\mathbf{n}}(\mathbf{t}) + \sigma \cdot \delta_n(t) \tag{5.4}$$

Where ω is the constant, $\boldsymbol{\lambda}$ is a vector of parameters associated with the explanatory variables $\mathbf{X}_{\mathbf{n}}(\mathbf{t})$, and σ is the parameter associated with the observation specific error term $\delta_n(t) \sim N(0,1)$. Relevant explanatory variables are the driver behaviour characteristics of the subject vehicle and of the leader, such as speed, relative speed, and distance headway (Fuller, 2011). The observation-specific error term captures unexplained variability between choice situations. The risk feeling and task difficulty evaluation conditional on the value of ϑ_n is calculated as follows in equations (5.5)-(5.7):

$$P(\mathrm{RFTDE}_n(t)=L|\vartheta_n) = \Phi\left(\frac{\mathrm{MinAc}_n(t) - \omega - \boldsymbol{\lambda} \cdot \mathbf{X}_{\mathbf{n}}(\mathbf{t})}{\sigma}\right) \tag{5.5}$$

$$P(\mathrm{RFTDE}_n(t)=Ac|\vartheta_n) = \Phi\left(\frac{\mathrm{MaxAc}_n(t) - \omega - \boldsymbol{\lambda} \cdot \mathbf{X}_{\mathbf{n}}(\mathbf{t})}{\sigma}\right) - \Phi\left(\frac{\mathrm{MinAc}_n(t) - \omega - \boldsymbol{\lambda} \cdot \mathbf{X}_{\mathbf{n}}(\mathbf{t})}{\sigma}\right) \tag{5.6}$$

$$P(\mathrm{RFTDE}_n(t)=H|\vartheta_n) = 1 - \Phi\left(\frac{\mathrm{MaxAc}_n(t) - \omega - \boldsymbol{\lambda} \cdot \mathbf{X}_{\mathbf{n}}(\mathbf{t})}{\sigma}\right) \tag{5.7}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standardized normal distribution. The parameters μ^H, τ, γ, ω, λ are estimated while σ is fixed to one and μ^L is fixed to zero for identification purposes. In this framework, the driver-specific error terms are estimated in both threshold equations to capture the impact of unobserved heterogeneity on both the minimum and maximum risk acceptable.

5.4.2 Level 2: choice of ACC system state (discrete choice)

Drivers who consider the RFTD lower than the minimum value acceptable choose to overrule the ACC by pressing the gas pedal (AAc), to maintain the system active and increase the target speed (AS+), or not to intervene (AL). This decision is formulated as a logit model, in which the utility functions *U* for driver *n* at time *t* are given by equations (5.8)-(5.10):

$$U_n^{AAc}(t) = \alpha^{AAc} + \boldsymbol{\beta}^{\mathbf{AAc}} \cdot \mathbf{X}_{\mathbf{n}}^{\mathbf{AAc}}(\mathbf{t}) + \gamma^{AAc} \cdot \vartheta_n + \varepsilon_n^{AAc}(t) \tag{5.8}$$

$$U_n^{AS+}(t) = \boldsymbol{\beta}^{\mathbf{AS+}} \cdot \mathbf{X}_{\mathbf{n}}^{\mathbf{AS+}}(\mathbf{t}) + \varepsilon_n^{AS+}(t) \tag{5.9}$$

$$U_n^{AL}(t) = \alpha^{AL} + \gamma^{AL} \cdot \vartheta_n + \varepsilon_n^{AL}(t) \tag{5.10}$$

where α^{AAc} and α^{AL} are alternative specific constants, $\boldsymbol{\beta}^{\mathbf{AAc}}$ and $\boldsymbol{\beta}^{\mathbf{AS+}}$ are vectors of parameters associated with the explanatory variables $\mathbf{X}_{\mathbf{n}}^{\mathbf{AAc}}(\mathbf{t})$ and $\mathbf{X}_{\mathbf{n}}^{\mathbf{AS+}}(\mathbf{t})$, γ^{AAc} and γ^{AL} are the parameters associated with the individual specific error term $\vartheta_n \sim N(0,1)$, and $\varepsilon_n^{AAc}(t)$, $\varepsilon_n^{AS+}(t)$, and $\varepsilon_n^{AL}(t)$ are i.i.d. Gumbel–distributed error terms. In the utility of not intervening in low risk conditions, the constant and the driver-specific error term are estimated while the explanatory variables are assumed to have an impact equal to zero for identification purposes (Choudhury, 2007; Choudhury et al., 2007). Relevant explanatory variables can include the driver behaviour characteristics of the subject vehicle and of its leader, variables related to the functioning of the system, characteristics of the freeway segment, and driver characteristics. The probability of choosing the ACC system state $k \in C_l$ with $C_l = \{AAc, AS+, AL\}$ in low risk situations is presented in equation (5.11):

$$P(Y_n(t) = k \mid RFTDE_n(t) = L, \vartheta_n) = \frac{\exp\left(\alpha^k + \boldsymbol{\beta}^{\mathbf{k}} \cdot \mathbf{X}_{\mathbf{n}}^{\mathbf{k}}(\mathbf{t}) + \gamma^k \cdot \vartheta_n\right)}{\sum_l \exp\left(\alpha^l + \boldsymbol{\beta}^{\mathbf{l}} \cdot \mathbf{X}_{\mathbf{n}}^{\mathbf{l}}(\mathbf{t}) + \gamma^l \cdot \vartheta_n\right)} \tag{5.11}$$

Drivers who consider the RFTD higher than the maximum value acceptable choose to deactivate the ACC (I) or to maintain the system active and decrease the target speed (AS-). This decision is formulated as a logit model, in which the utility functions *U* for driver *n* at time *t* are given by equations (5.12)-(5.13):

$$U_n^{I}(t) = \alpha^{I} + \boldsymbol{\beta}^{\mathbf{I}} \cdot \mathbf{X}_{\mathbf{n}}^{\mathbf{I}}(\mathbf{t}) + \gamma^{I} \cdot \vartheta_n + \varepsilon_n^{I}(t) \tag{5.12}$$

$$U_n^{AS-}(t) = 0 + \varepsilon_n^{AS-}(t) \tag{5.13}$$

where α^I is an alternative specific constant, $\boldsymbol{\beta}^{\mathbf{I}}$ is the vector of parameters associated with the explanatory variables $\mathbf{X}_{\mathbf{n}}^{\mathbf{I}}(\mathbf{t})$, γ^I is the parameters associated with the individual specific error term $\vartheta_n \sim N(0,1)$, and $\varepsilon_n^{I}(t)$, and $\varepsilon_n^{AS-}(t)$ are i.i.d. Gumbel – distributed error terms. Relevant explanatory variables are similar to those listed above for low risk conditions. The probability of choosing the ACC system state $i \in C_h$ with $C_h = \{I, AS-\}$ in high risk situations is presented in equation (5.14):

$$P(Y_n(t) = i \mid RFTDE_n(t) = H, \vartheta_n) = \frac{\exp\left(\alpha^i + \boldsymbol{\beta}^{\mathbf{i}} \cdot \mathbf{X}_{\mathbf{n}}^{\mathbf{i}}(\mathbf{t}) + \gamma^i \cdot \vartheta_n\right)}{\sum_h \exp\left(\alpha^h + \boldsymbol{\beta}^{\mathbf{h}} \cdot \mathbf{X}_{\mathbf{n}}^{\mathbf{h}}(\mathbf{t}) + \gamma^h \cdot \vartheta_n\right)} \tag{5.14}$$

The parameters α, β, γ are estimated and can be assumed to have a different value in each level of feeling of risk and in each utility function.

5.4.3 Level 2: choice of ACC target speed regulation (continuous choice)

ACC target speed regulations are observed only when drivers choose to regulate the ACC target speed. The magnitude of the regulation depends on the choice of increasing or decreasing the ACC target speed. In this framework, decisions to increase or decrease the ACC target speed are captured explicitly (i.e., if a driver chooses to increase the ACC target speed, the increase will be always positive). To represent this process, the error term is assumed to be a positive random variable. In this case study, the absolute values of the observed ACC target speed increase (*ACCTarSpeed+)* and decrease (*ACCTarSpeed-*) are log-transformed. The regression equations of the ACC target speed increase (Y_n^{TS+}) and decrease (Y_n^{TS-}) conditional upon choosing to increase or decrease the ACC target speed are given in equations (5.15)-(5.16):

$$Y_n^{TS+}(t) = \eta^{TS+} + \boldsymbol{\xi}^{\mathbf{TS+}}\cdot\mathbf{X}_{\mathbf{n}}^{\mathbf{TS+}}(\mathbf{t}) + \sum_{j\neq AS+} \varphi_j^{TS+}\cdot C_j^{TS+} + \gamma^{TS+}\cdot\vartheta_n + \omega^{TS+}\cdot\upsilon_n^{TS+}(t) \tag{5.15}$$

$$Y_n^{TS-}(t) = \eta^{TS-} + \boldsymbol{\xi}^{\mathbf{TS-}}\cdot\mathbf{X}_{\mathbf{n}}^{\mathbf{TS-}}(\mathbf{t}) + \varphi_I^{TS-}\cdot C_I^{TS-} + \gamma^{TS-}\cdot\vartheta_n + \omega^{TS-}\cdot\upsilon_n^{TS-}(t) \tag{5.16}$$

Where $\eta^{TS+(-)}$ is the constant, $\boldsymbol{\xi}^{\mathbf{TS+(-)}}$ is the vector of parameters associated with the explanatory variables $\mathbf{X}_{\mathbf{n}}^{\mathbf{TS+(-)}}(\mathbf{t})$, φ_j^{TS+} with $j \in \{AAc, AL\}$ and φ_I^{TS-} are the parameters associated with the selectivity correction terms C_j^{TS+} and C_I^{TS-} respectively, $\gamma^{TS+(-)}$ is the parameter associated with the individual specific error term ϑ_n~N(0,1), $\omega^{TS+(-)}$ is the parameter associated with the observation specific error term $\upsilon_n^{TS+(-)}(t) \sim N(0,1)$. Relevant explanatory variables can include the driver behaviour characteristics of the subject vehicle and of its leader, variables related to the functioning of the system, characteristics of the freeway segment, and driver characteristics. The selectivity correction terms C_j^{TS+} and $C_I^{TS-}$are given in equations (5.17)-(5.18):

$$C_j^{TS+} = \left[\frac{P^j\cdot \ln(P^j)}{1-P^j} + \ln\left(P^{AS+}\right)\right] \tag{5.17}$$

$$C_I^{TS-} = \left[\frac{P^I\cdot \ln(P^I)}{1-P^I} + \ln\left(P^{AS-}\right)\right] \tag{5.18}$$

Where P^{AAc}, P^{AL} and P^{AS+} are the choice probabilities to overrule the ACC system, not to intervene, and to increase the target speed in the low-risk logit model (5.11), and P^I and P^{AS-} are the choice probabilities to deactivate and decrease the target speed in the high-risk logit model (5.14). The inclusion of the selectivity correction terms into the regression equations corrects for the system state selectivity bias under the assumption that the choice probabilities are logit and the error terms are normally distributed (Dubin and McFadden, 1984; Train, 1986). These correction terms capture unobserved factors that influence both the probability of the system state choice and the magnitude of the target speed regulation. The probability density functions of the target speed increase and decrease conditional on the choices to decrease or increase the ACC target speed are given by equations (5.19)-(5.20):

$$P\{Y_n^{TS+}(t) = \log\left(\left|ACCTarSpeed_n^{+}(t)\right|\right) \mid Y_n(t) = AS+, RFTDE_n(t) = L,\ \vartheta_n\}$$
$$= \frac{1}{\omega^{TS+}}\Phi\left(\frac{\log(\left|ACCTarSpeed_n^{+}(t)\right|) - \eta^{TS+} - \boldsymbol{\xi}^{\mathbf{TS+}}\cdot\mathbf{X}(\mathbf{t}) - \sum_{j\neq AS+}\varphi_j^{TS+}\cdot C_j^{TS+} - \gamma^{TS+}\cdot\vartheta_n}{\omega^{TS+}}\right) \tag{5.19}$$

$$P\{Y_n^{TS-}(t) = \log\left(\left|ACCTarSpeed_n^{-}(t)\right|\right) \mid Y_n(t) = AS-,\ RFTDE_n(t) = H,\ \vartheta_n\}$$
$$= \frac{1}{\omega^{TS-}}\Phi\left(\frac{\log(\left|ACCTarSpeed_n^{-}(t)\right|) - \eta^{TS-} - \boldsymbol{\xi}^{\mathbf{TS-}}\cdot\mathbf{X}(\mathbf{t}) - \varphi_I^{TS-}\cdot C_I^{TS-} - \gamma^{TS-}\cdot\vartheta_n}{\omega^{TS-}}\right) \tag{5.20}$$

The parameters η, ξ, φ, γ, ω are estimated and can assume a different value in each regression equation.

5.5 Maximum likelihood estimation of the integrated continuous-discrete choice model

The parameters of the choice models and of the regression models are estimated simultaneously with full information maximum likelihood methods. Given $Y_n(t)$ the indicator associated with the system state choice, $Y_n^{TS}(t)$ the indicator associated with the observed values of the ACC target speed regulations, and $RFTDE_n(t)$ the indicator associated with the unobservable risk feeling and task difficulty evaluation, the unconditional probability of deactivating (or overruling) the system (5.21), of increasing (or decreasing) the ACC target speed (5.22), and of not intervening (5.23) in a single observation are given as follows:

$$P(Y_n(t) \mid \vartheta_n) = P(Y_n(t) \mid RFTDE_n(t),\ \vartheta_n) \cdot P(RFTDE_n(t) \mid \vartheta_n) \tag{5.21}$$

$$P\left(Y_n(t), Y_n^{TS}(t) \mid \vartheta_n\right) = P\left(Y_n^{TS}(t) \mid Y_n(t), RFTDE_n(t), \vartheta_n\right) \cdot P(Y_n(t) \mid RFTDE_n(t),\ \vartheta_n) \cdot P(RFTDE_n(t) \mid \vartheta_n) \tag{5.22}$$

$$P(Y_n(t) \mid \vartheta_n) = P(RFTDE_n(t)=Ac \mid \vartheta_n) + P(Y_n(t)=AL \mid RFTDE_n(t)=L,\ \vartheta_n) \cdot P(RFTDE_n(t)=L \mid \vartheta_n) \tag{5.23}$$

Where $P\left(Y_n^{TS}(t) \mid \cdot\right)$ is presented in equations (5.19)-(5.20), $P(Y_n(t) \mid \cdot)$ in equations (5.11) and (5.14), and $P(RFTDE_n(t) \mid \cdot)$ in equations (5.5)-(5.7). Notably, the unconditional probability of not intervening is the sum of the probabilities of perceiving the feeling of risk as to be acceptable and of not intervening when the feeling of risk is lower than the minimum risk acceptable. This formulation allows decisions of not intervening to arise from two different levels of perceived risk (acceptable and low) and captures explicitly drivers' propensity to not intervene when the system is active (Greene et al., 2013). The joint probability of the *T* observations over time for the same driver is given by equation (5.24):

$$P\left(Y_n(1), Y_n^{TS}(1), \ldots, Y_n(T), Y_n^{TS}(T) \mid \vartheta_n\right) = \prod_{t=1}^{T} P\left(Y_n(t), Y_n^{TS}(t) \mid \vartheta_n\right) \tag{5.24}$$

The unconditional joint probability of the observations for each driver is obtained by integrating over the distribution of ϑ_n, which is assumed to be standard normal, as presented in equation (5.25):

$$P\left(Y_n(1), Y_n^{TS}(1), \ldots, Y_n(T), Y_n^{TS}(T)\right) = \int_{-\infty}^{+\infty} P\left(Y_n(1), Y_n^{TS}(1), \ldots, Y_n(T), Y_n^{TS}(T) \mid \vartheta\right) \Phi(\vartheta)\, d\vartheta \tag{5.25}$$

The integral is calculated using Monte-Carlo integration. The random draws are generated using the 'Modified Latin Hypercube Sampling' method (Hess et al., 2006). The log-likelihood function for all drivers 1, …, N is given by equation (5.26):

$$LL = \sum_{n=1}^{N} \ln\left[P\left(Y_n(1), Y_n^{TS}(1), \ldots, Y_n(T), Y_n^{TS}(T)\right)\right] \tag{5.26}$$

5.6 Case study

The model can be estimated using driving behaviour data with ACC and information on individual drivers. Section 5.6.1 briefly describes the on-road experiment, the characteristics of the ACC system, and the participants (for a detailed description, see Varotto et al. (2017)). Section 5.6.2 presents the analysis of the data to explore the conditions in which drivers resumed manual control and regulated the target speed. Section 5.6.3 discusses the estimation results of the model and the impact of the explanatory variables on the choice probabilities. Section 5.6.4 proposes *in-sample-out-of-time* and *out-of-sample-in-time* validation analyses of the model estimated.

5.6.1 Data collection

The on-road experiment consisted of a single drive (46-km long) on a pre-set test route on the A99 in Munich. The test route comprised four freeway segments mostly composed of three lanes per direction. In the first freeway segment, participants tested the system and found their preferred gap setting. During the experiment on the remaining three freeway segments (35.5 km), participants were instructed to drive as they normally would, regulating the target speed settings and resuming manual control at any time.

The research vehicle used was a BMW 5 Series equipped with a regular version of full-range ACC, which maintains a target speed at speeds between 0 and 210 km/h and a target time headway at speeds higher than 30 km/h. The range of the radar is 120 m. The target time headways that can be set are 1.0, 1.4, 1.8, and 2.2 s. The maximum acceleration and deceleration supported by the system are 3 m/s^2 and –3 m/s^2. When the system is active, it is possible to set a target speed and time headway by using the switches. Drivers can resume manual control temporarily by pressing the gas pedal (transition to *Active and accelerate*) and can deactivate the system by pressing the on/off button or the brake (transition to *Inactive).*

Twenty-three participants recruited among BMW employees in Munich completed the experiment. Fifteen participants were male, and eight were female. Participants had between 3 and 33 years of driving experience. Six participants had never used ADAS (Advanced Driving Assistance Systems) before the experiment (no experience), nine had driven with ADAS less often than once a month during the previous year (medium experience), and eight once a month or more often (high experience). None of them had been directly working on the development of the ACC system. Before the experiment, participants were instructed on the specifications of the system, signed an informed consent form, and filled a questionnaire reporting demographic characteristics (Kyriakidis et al., 2014), driving experience (Kyriakidis et al., 2014), experience with ADAS, and driving styles (Taubman-Ben-Ari et al., 2004). The experiment was carried out during the peak hours of the morning (7-9 am) and of the evening (4-6 pm, 6-8 pm) from June 29th to July 9th 2015. Participants drove between 45 and 90 minutes, based on the traffic flow conditions. Speed, acceleration, distance headway (from radar), speed of the leader (from radar), ACC system settings and state, and GPS position were measured and registered in the Controller Area Network (CAN) of the instrumented vehicle. After the experiment, participants filled a questionnaire about the usage of the ACC system, workload experienced (Byers et al., 1989; Kyriakidis et al., 2014), and the usefulness and satisfaction of the system (Kyriakidis et al., 2014; Van der Laan et al., 1997). The empirical cumulative distribution functions of the driver characteristics reported in the questionnaire are presented in Appendix B, Figure B.1. Drivers reported higher scores on the patient and careful driving style than on the other driving styles, which is similar to previous findings (Taubman-Ben-Ari et al., 2004). Drivers reported low to medium levels of workload while driving with ACC and medium to high levels of usefulness and satisfaction with the system.

5.6.2 Data analysis

The data collected in the experiment (23 drives of 35.5 km) were analysed to investigate the situations in which drivers resumed manual control (presented in Varotto et al. (2017)) and regulated the ACC target speed. Control transitions initiated by the system, and transitions or target speed regulations that occurred between 10 s before and 10 s after a lane change were not analysed. The data were reduced to 1 Hz resolution, resulting in 31,165 observations. This study analyses 23,568 observations of 1 s in which a leader is detected by the radar (120 m) and the ACC system is active. 106 observations (0.45%) were immediately followed by a DIDC transition to Active and accelerate (overruling), 210 (0.89%) by an increase in the ACC target speed, 55 (0.23%) by a DIDC transition to Inactive (deactivations), 125 (0.53%) by a decrease in the ACC target speed, and 23,072 (97.9%) by neither transitions nor speed regulations. Drivers transferred to Active and accelerate from 0 to 26 times (M=4.61, SD=5.88), increased the ACC target speed from 1 to 24 times (M=9.13, SD=5.34), transferred to Inactive from 0 to 7 times (M=2.39, SD=1.83), and decreased the ACC target speed from 1 to 11 times (M=5.43, SD=2.86).

To gain insight into the conditions in which control transitions and speed regulations were initiated, the empirical distribution functions of the driver behaviour characteristics were analysed when neither transitions nor speed regulations happened, when the ACC was deactivated or overruled, and when the ACC target speed was reduced or increased (Appendix B, Figure B.2). The mean and the standard deviation of these variables are presented in Table 5.1. The similarity of the distributions between the different groups was tested using two-sample Kolmogorov-Smirnov tests (Appendix B, Table B.1). Most transitions to Active and accelerate were initiated a few seconds after the activation. At high speeds, deactivations and target speed reductions occurred more often than overruling actions and target speed increments. When the vehicle decelerated, transitions to Active and accelerate happened more often than target speed increments. Deactivations happened more often than target speed reductions when the target speed was lower than the actual speed. Overruling actions occurred more often than target speed increments when the target speed was higher than the actual speed. On average, deactivations and target speed reductions were associated with larger distance headways. Deactivations and target speed reductions happened most often when the subject vehicle was faster than the leader, while target speed increments happened most often when the subject vehicle was slower. Most deactivations occurred when the subject vehicle accelerated more than the leader. Most target speed regulations ranged between -20 and +20 km/h. In addition, cut-in manoeuvres were detected as described in Varotto et al. (2017). These findings suggest that the driver behaviour characteristics of the subject vehicle and of the leader may impact significantly drivers' decisions to regulate the target speed and to resume manual control.

Control transitions and target speed regulations occurred more often in freeway sections where vehicles change lanes more frequently, potentially disturbing traffic flow. Drivers deactivated the system more often in proximity to an on-ramp and before exiting the freeway (Varotto et al., 2017). Drivers overruled the system or increased the ACC target speed more often between ramps that are closer than 600 m (FGSV, 2008) and in proximity to an on-ramp. Drivers showed significant differences in resuming manual control and regulating the

ACC target speed based on their individual characteristics. Correlation analysis was conducted to explore the relations between the driver characteristics, the number of transitions executed, and the magnitude of the target speed regulation selected for each driver. Drivers who deactivated the ACC more often also overruled the system more often. Drivers inexperienced with ADAS chose smaller target speed increments. Individual characteristics such as gender and age were correlated significantly with driving styles, workload experienced during the drive, and usefulness and satisfaction of the ACC. Further analysis is needed to investigate moderate correlation results.

Table 5.1: Mean and standard deviation of the driver behaviour characteristics when drivers transfer the ACC to Inactive (I), decrease the ACC target speed (AS-), maintain the ACC Active (A), increase the ACC target speed (AS+), and transfer to Active and accelerate (AAc)

Variables	Description	I	AS-	A	AS+	AAc
Time after last activation	Time after the ACC has been activated in s	76.0 (83.2)	102 (117)	153 (156)	115 (130)	50.3 (128)
Speed	Speed of the subject vehicle in km/h	94.8 (40.9)	93.1 (34.5)	72.6 (38.0)	82.1 (28.9)	86.5 (36.9)
Acceleration	Acceleration of the subject vehicle in m/s^2	-0.0491 (0.549)	-0.0935 (0.480)	-0.00294 (0.390)	0.0956 (0.332)	-0.272 (0.462)
Target time headway – time headway	Difference between the ACC target time headway and the time headway (front bumper to rear bumper) in s	-0.574 (0.758)	-0.546 (0.682)	-0.361 (0.558)	-0.585 (0.710)	-0.160 (0.780)
Target speed – speed	Difference between the ACC target speed and the subject vehicle speed in km/h	16.2 (22.2)	18.5 (21.0)	25.8 (25.0)	8.97 (12.1)	20.2 (24.9)
Distance headway	Distance headway (front bumper to rear bumper) in m	49.8 (27.5)	49.8 (24.2)	36.5 (22.9)	44.7 (22.0)	39.1 (23.1)
Relative speed	Speed difference between leader speed and subject vehicle in km/h	-7.84 (11.8)	-3.16 (8.51)	-0.829 (5.69)	2.62 (6.36)	-1.04 (6.33)
Relative acceleration	Acceleration difference between the leader and the subject vehicle in m/s^2	-0.287 (0.609)	-0.0234 (0.517)	0.0140 (0.375)	0.0618 (0.377)	0.225 (0.479)

5.6.3 Estimation results

In this case study, it was assumed that only one decision happens within a 1-s interval. This interval of time is similar to the mean reaction time between the recognition of a stimulus and the execution of the response in literature (Toledo, 2003). The decisions are related to the driver behaviour characteristics recorded at the beginning of the interval. Multiple 1-s observations, repeated over time, are available for each driver (panel data). Notably, the model specification presented in this section is the result of an intensive modelling process in which several specifications and model structures were compared based on statistical tests. The model was estimated using the software PythonBiogeme (Bierlaire, 2016). All model components were estimated simultaneously using full information maximum likelihood methods as described in Section 5.5. The log likelihood and the goodness of fit indicators are presented in Table 5.2 and the estimation results in Table 5.3-Table 5.5. Most parameters are statistically significant at the 95% confidence level. The next sections discuss the estimation results of each model component and the impact of the explanatory variables on the unconditional choice probabilities.

Table 5.2: Statistics of the continuous-discrete choice model

Statistics	
Number of drivers	23
Number of observations	23,568
Number of constants	8
Number of parameters associated with explanatory variables (K)	28
Constant log likelihood $L(c)$	-3496
Final log likelihood $L(\hat{\beta})$	-3078
Adjusted likelihood ratio index (rho-bar-squared) $\bar{\rho}^2 = 1 - \frac{(L(\hat{\beta}) - K)}{L(c)}$	0.112

Risk feeling and task difficulty evaluation

In the ordered probit model, the risk feeling and task difficulty RFTD are influenced by the driver behaviour characteristics of the subject vehicle and of its leader as shown in equation (5.27):

$$RFTD_n(t) = \omega + \lambda_{\frac{Speed}{DHW}} \cdot \frac{Speed(t)}{DHW(t)} + \lambda_{RelSpeed} \cdot RelSpeed(t) + \lambda_{RelAcc} \cdot RelAcc(t) + \lambda_{AntCutIn3} \cdot AntCutIn3(t) + \delta_n(t) \quad (5.27)$$

Where ω is the constant, $\lambda_{\frac{Speed}{DHW}}, \lambda_{RelSpeed}, \lambda_{RelAcc}, \lambda_{AntCutIn3}$ are the parameters associated with the explanatory variables listed in Table 5.3, and $\delta_n(t) \sim N(0,1)$ is the observation specific error term. Speed is divided by distance headway because drivers are assumed to be more sensitive to changes in risk feelings at short distance headways and at high speeds. In addition, speed and distance headway are highly correlated. The lowest and the highest acceptable risk are functions of the functioning of the ACC system and driver characteristics as presented in equations (5.28)-(5.29):

$$\mathrm{MinAc}_n(t) = \exp\left(0 + \tau^{L}_{\mathrm{TimeAct}} \cdot \log\left(\mathrm{TimeAct}(t)\right) + \tau^{L}_{\mathrm{PatCar}} \cdot \mathrm{PatCar}_n + \gamma^{L} \cdot \vartheta_n\right) \tag{5.28}$$

$$\mathrm{MaxAc}_n(t) = \mathrm{MinAc}_n(t) + \exp\left(\mu^{H} + \tau^{H}_{\mathrm{TimeAct}} \cdot \log\left(\mathrm{TimeAct}(t)\right) + \tau^{H}_{\mathrm{PatCar}} \cdot \mathrm{PatCar}_n + \gamma^{H} \cdot \vartheta_n\right) \tag{5.29}$$

where μ^H is the constant, $\tau^L_{TimeAct}$, τ^L_{PatCar}, $\tau^H_{TimeAct}$, and τ^H_{PatCar} are the parameters associated with the explanatory variables listed in Table 5.3, γ^L and γ^H are the parameters associated with the individual specific error term $\vartheta_n \sim N(0,1)$. The logarithmic transformation of the time after last activation is consistent with the empirical findings and showed a significant better fit than a linear specification. The road location, the other driving styles (reckless and careless, angry and hostile, and anxious), gender, age, experience with ADAS, workload, and usefulness and satisfaction with ACC did not influence significantly the acceptable range.

The estimation results in Table 5.3 show that drivers perceive higher risk at higher speeds and at shorter distance headways. In addition, they perceive higher risks when they are faster (negative relative speed) and accelerate more (negative relative acceleration) than the leader, and when they suppose that a vehicle will cut in during the next three seconds. To analyse the impact of variations in the explanatory variables in the threshold equations, the lowest and highest risk acceptable with ACC active and the mean feeling of risk were calculated in observations in which only one explanatory variable was altered while maintaining all the other variables fixed. In the baseline observation, the driver was assumed to have experience with ADAS and a score on the patient and careful driving style equal to the mean in this sample. The speed was equal to 87.2 km/h, the ACC target speed 102 km/h, the acceleration -0.0467 m/s^2, the distance headway 45.3 m, the relative speed -0.781 km/h, and the relative acceleration 0.0365 m/s^2. The ACC system had been activated for 94 s and cut-in manoeuvres, ramps, and exits did not influence the driver. These values were selected based on the average conditions of the control transitions and target speed regulations observed. The results are presented in Figure 5.2. Few seconds after the system has been activated (Figure 5.2 *a*), drivers showed a higher minimum risk acceptable and a lower maximum risk acceptable (i.e., drivers' acceptable range with the ACC active is smaller). This means that, immediately after activation, drivers press the gas pedal or increase the target speed when the risk feeling is higher in low risk situations and deactivate or decrease the speed when the risk is lower in high risk situations. Interestingly, drivers who reported a high score on the patient and careful driving style (Figure 5.2 *b*) showed a higher minimum risk acceptable and a lower maximum risk acceptable (their acceptable range with the ACC active is smaller). This result means that patient and careful drivers resume manual control or regulate the target speed when the risk feeling is higher in low risk situations and when it is lower in high risk situations. The driver specific error term has a different effect on the minimum and on the maximum acceptable risk (Figure 5.2 *c*): certain drivers showed a higher risk acceptable in high risk situations and a lower risk acceptable in low risk situations (larger acceptable range with the ACC active), while others showed a higher risk acceptable in high risk situations and a higher risk acceptable in low risk situations (smaller acceptable range with the ACC active). This means that drivers, who deactivate or decrease the speed when the risk feeling is higher in high risk situations, can press the gas pedal or increase the target speed in low risk situations when the risk feeling is lower or when it is higher.

Table 5.3: Estimation results of the continuous-discrete choice model: risk feeling and task difficulty evaluation

Variable	Description	Parameter	Estimate	Robust t-stat.	Robust p-value
Risk feeling and task difficulty					
-	Constant risk feeling and task difficulty with ACC active	ω	1.76	8.55	<0.005
Speed/DHW	Speed of the subject vehicle in km/h divided by distance headway (front bumper to rear bumper) in m	$\lambda_{Speed/DHW}$	0.0426	1.52	0.13
RelSpeed	Relative speed (leader speed – subject vehicle speed) in km/h	$\lambda_{RelSpeed}$	-0.0381	-9.64	<0.005
RelAcc	Relative acceleration (leader acceleration – subject vehicle acceleration) in m/s^2	λ_{RelAcc}	-0.249	-3.87	<0.005
AntCutIn3	Number of cut-ins in the following three seconds	$\lambda_{AntCutIn3}$	0.528	7.12	<0.005
Lowest and highest acceptable risk					
-	Constant highest acceptable risk with ACC active	μ^H	1.05	18.74	<0.005
TimeAct	Logarithm of time after the activation of ACC in s	$\tau^L_{TimeAct}$	-0.125	-3.98	<0.005
TimeAct	Logarithm of time after the activation of ACC in s	$\tau^H_{TimeAct}$	0.0646	13.54	<0.005
PatCar	Score on the driving-style factor 'Patient and careful'[1] (MDSI (Taubman-Ben-Ari et al., 2004))	τ^L_{PatCar}	0.337	1.32	0.19
PatCar	Score on the driving-style factor 'Patient and careful'[1] (MDSI (Taubman-Ben-Ari et al., 2004))	τ^H_{PatCar}	-0.119	-2.03	0.04
ϑ_n	Individual-specific error term	γ^L	0.383	3.31	<0.005
ϑ_n	Individual-specific error term	γ^H	-0.0705	-5.15	<0.005

Note: [1] variable centred on the mean value between drivers.

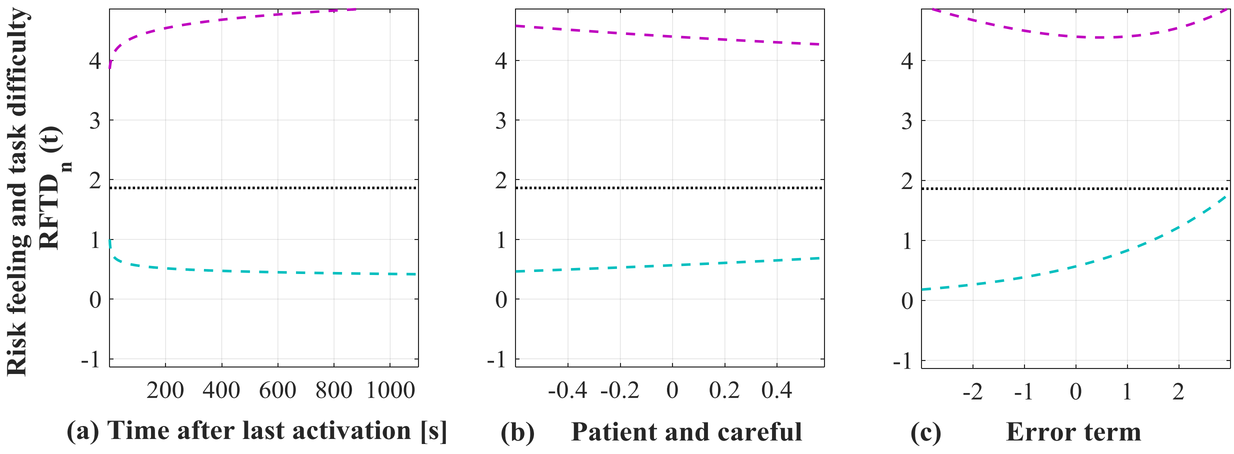

Figure 5.2: Impact of the explanatory variables and of the driver specific error term on the minimum (light blue dashed line) and on the maximum (purple dashed line) risk acceptable with ACC active, compared to the mean feeling of risk and task difficulty (black dotted line). The variables are listed as follows: (a) time after last activation, (b) patient and careful driving style (centred on the mean value between drivers), and (c) driver specific error term.

ACC system state choice

In low risk situations, the utility functions to overrule the ACC by pressing the gas pedal (AAc), to maintain the system active and increase the target speed (AS+), and not to intervene (AL) are influenced by the driver behaviour characteristics of the subject vehicle and of its leader, and by the functioning of the ACC system as shown in equations (5.30)-(5.32):

$$U_n^{AAc}(t) = \alpha^{AAc} + \beta_{TimeAct}^{AAc} \cdot \log\big(TimeAct(t)\big) + \beta_{Acc}^{AAc} \cdot Acc(t)$$

$$+ \beta_{AntCutIn3}^{AAc} \cdot AntCutIn3(t) + \gamma^{AAc} \cdot \vartheta_n + \varepsilon_n^{AAc}(t) \tag{5.30}$$

$$U_n^{AS+}(t) = \beta_{DiffTarSpeed}^{AS+} \cdot DiffTarSpeed(t) + \varepsilon_n^{AS+}(t) \tag{5.31}$$

$$U_n^{AL}(t) = \alpha^{AL} + \gamma^{I,AL} \cdot \vartheta_n + \varepsilon_n^{AL}(t) \tag{5.32}$$

where α^{AAc} and α^{AL} are alternative specific constants, $\beta_{TimeAct}^{AAc}$, β_{Acc}^{AAc}, $\beta_{AntCutIn3}^{AAc}$, $\beta_{DiffTarSpeed}^{AS+}$ are the parameters associated with the explanatory variables in Table 5.4, γ^{AAc} and $\gamma^{I,AL}$ are the parameters associated with the individual specific error term $\vartheta_n \sim N(0,1)$, and $\varepsilon_n^{AAc}(t)$, $\varepsilon_n^{AS+}(t)$, and $\varepsilon_n^{AL}(t)$ are i.i.d. Gumbel–distributed error terms. The specification proposed, which includes the alternative not to intervene in low risk situations, resulted in a considerable improvement in goodness of fit compared to a similar specification in which drivers could choose only to overrule the ACC system or to increase the target speed in low risk situations. This means that drivers showed a propensity to maintain the ACC active and do not regulate the target speed in low risk situations. Time after activation, acceleration, and expected cut-ins had a non-significant impact on choices to increase the target speed. The other explanatory variables described in Section 5.6.2 did not impact significantly the choice to increase the target speed or to overrule the ACC.

In high risk situations, the utility functions to deactivate the ACC (I) or to decrease the target speed (AS-) are influenced by the driver behaviour characteristics of the subject vehicle and of its leader, by the functioning of the ACC system, and by characteristics of the freeway segment as shown in equations (5.33)-(5.34):

$$U_n^I(t) = \alpha^I + \beta^I_{DiffTarSpeed} \cdot DiffTarSpeed(t) + \beta^I_{RelAcc} \cdot RelAcc(t)$$

$$+ \beta^I_{OnRamp} \cdot OnRamp(t) + \beta^I_{Exit} \cdot Exit(t) + \gamma^{I,AL} \cdot \vartheta_n + \varepsilon_n^I(t) \quad (5.33)$$

$$U_n^{AS-}(t) = 0 + \varepsilon_n^{AS-}(t) \quad (5.34)$$

where α^I is an alternative specific constant, $\beta^I_{DiffTarSpeed}$, β^I_{RelAcc}, β^I_{OnRamp}, β^I_{Exit} are the parameters associated with the explanatory variables in Table 5.4, $\gamma^{I,AL}$ is the parameter associated with the individual specific error term $\vartheta_n \sim N(0,1)$, and $\varepsilon_n^I(t)$, and $\varepsilon_n^{AS-}(t)$ are i.i.d. Gumbel–distributed error terms. A similar specification including the alternative not to intervene in high risk situations did not result in a significant improvement in the goodness of fit. This means that drivers showed a more consistent behaviour in high risk situations than in low risk situations. The other explanatory variables in Section 5.6.2 did not influence significantly the choice to deactivate the ACC.

The estimation results in Table 5.4 show that, in low risk situations, the alternative specific constant of overruling the ACC system by pressing the gas pedal is non-significant while the alternative specific constant of not intervening is significant and positive. This result means that drivers are more likely not to intervene than to overrule the ACC or to increase the target speed everything else being equal. In high risk situations, the alternative specific constant of deactivating the system is negative. This suggests that drivers are more likely to decrease the target speed than to deactivate the system everything else being equal. In low risk situations, drivers are more likely to increase the ACC target speed when the ACC target speed is lower than the actual speed and to overrule the ACC few seconds after the system has been activated. Drivers are more likely to overrule the system by pressing the gas pedal when the ACC acceleration is low and when they expect cut-ins during the next three seconds. In high risk situations, drivers are more likely to deactivate the ACC when the target speed is lower than the actual speed and when they accelerate more than the leader (negative relative acceleration). In addition, drivers are influenced by the road location and are more likely to deactivate the ACC in proximity to an on-ramps, between two ramps, and before exiting the freeway (similar to findings in Pereira et al. (2015)). The driver-specific error term has a significant effect on the system state choices in high and low risk situations, meaning that certain drivers are more likely to resume manual control or not to intervene in low risk situations than others. The effect of this term on overruling the ACC was larger than the effect on deactivations and of not intervening in low risk situations, which did not differ significantly. This means that drivers showed a larger variability in overruling the system by pressing the gas pedal.

Table 5.4: Estimation results of the continuous-discrete choice model: ACC system state choice

Variable	Description	Parameters	Estimate	Robust t-stat.	Robust p-value
Low risk situations					
-	Alternative specific constant	α^{AAc}	0.195	0.30	0.76
-	Alternative specific constant	α^{AL}	1.41	3.57	<0.005
TimeAct	Logarithm of time after the activation of ACC in s	$\beta^{AAc}_{TimeAct}$	-0.72	-6.68	<0.005
DiffTarSpeed	Difference between the ACC target speed and the speed of the subject vehicle in km/h	$\beta^{AS+}_{DiffTarSpeed}$	-0.0622	-7.50	<0.005
Acc	Acceleration of the subject vehicle in m/s^2	β^{AAc}_{Acc}	-2.04	-7.18	<0.005
AntCutIn3	Number of cut-ins in the following three seconds	$\beta^{AAc}_{AntCutIn3}$	1.45	2.42	0.02
ϑ_n	Individual-specific error term	γ^{AAc}	1.00	2.99	<0.005
ϑ_n	Individual-specific error term	$\gamma^{AL,I}$	0.470	1.77	0.08
High risk situations					
-	Alternative specific constant	α^{I}	-1.51	-3.53	<0.005
DiffTarSpeed	Difference between the ACC target speed and the speed of the subject vehicle in km/h	$\beta^{I}_{DiffTarSpeed}$	-0.0156	-1.80	0.07
RelAcc	Relative acceleration (leader acceleration – subject vehicle acceleration) in m/s^2	β^{I}_{RelAcc}	-1.11	-2.65	0.01
OnRamp	Binary variable equal to 1 when the drivers are in the mainline close to an on-ramp, or between two ramps closer than 600 m (FGSV, 2008)	β^{I}_{OnRamp}	1.30	3.70	<0.005
Exit	Binary variable equal to 1 when the drivers are in the mainline closer than 1600 m to the exit (first exit sign)	β^{I}_{Exit}	3.08	5.21	<0.005
ϑ_n	Individual-specific error term	$\gamma^{AL,I}$	0.470	1.77	0.08

ACC target speed regulation choice

The regression equations of the ACC target speed increase (Y_n^{TS+}) and decrease (Y_n^{TS-}) are influenced significantly by the target speed set in the system, by the relative speed and by driver characteristics as shown in equations (5.35)-(5.36):

$$Y_n^{TS+}(t) = \eta^{TS+} + \xi_{NoviceADAS}^{TS+} \cdot NoviceADAS_n + \varphi_{AAc}^{TS+} \cdot C_{AAc}^{TS+} + \varphi_{AL}^{TS+} \cdot C_{AL}^{TS+} + \gamma^{TS} \cdot \vartheta_n + \omega^{TS+} \cdot \upsilon_n^{TS+}(t) \tag{5.35}$$

$$Y_n^{TS-}(t) = \eta^{TS-} + \xi_{DiffTarSpeed}^{TS-} \cdot DiffTarSpeed(t) + \xi_{RelSpeed}^{TS-} \cdot RelSpeed(t) + \varphi_I^{TS-} \cdot C_I^{TS-} + \gamma^{TS} \cdot \vartheta_n + \omega^{TS-} \cdot \upsilon_n^{TS-}(t) \tag{5.36}$$

Where η^{TS+} and η^{TS-} are constants, $\xi_{NoviceADAS}^{TS+}$, $\xi_{DiffTarSpeed}^{TS-}$, $\xi_{RelSpeed}^{TS-}$ are the parameters associated with the explanatory variables listed in Table 5.5, φ_{AAc}^{TS+}, φ_{AL}^{TS+} and φ_I^{TS-} are the parameters associated with the selectivity correction terms C_{AAc}^{TS+}, C_{AL}^{TS+}, and C_I^{TS-}, γ^{TS} is the parameter associated with the individual specific error term $\vartheta_n \sim N(0,1)$, and ω^{TS+} and ω^{TS-} are the parameters associated with the observation specific error terms $\upsilon_n^{TS+} \sim N(0,1)$ and $\upsilon_n^{TS-}(t) \sim N(0,1)$. The logarithmic transformation of the ACC target speed regulation is consistent with the empirical findings and showed a significant improvement in goodness of fit compared to a linear specification. The relative speed and the difference between the target speed and the actual speed did not impact significantly the ACC target speed increments. Experience with ADAS did not influence significantly the target speed decrements. Gender, age, driving styles, workload, and usefulness and satisfaction with ACC did not influence significantly the magnitude of the ACC target speed regulations.

The estimation results in Table 5.5 show that drivers select a larger ACC target speed decrement when the ACC target speed is higher than the current speed and when they are faster than the leader (negative relative speed). Drivers inexperienced with ADAS prefer smaller ACC target speed increments. The selectivity correction terms have a significant impact on the ACC target speed increments. Drivers choose larger ACC target speed increments in situations in which they are more likely to overrule the system by pressing the gas pedal and less likely not to intervene. This means that, everything else being equal, the magnitude of the increment is positively correlated with the choice probability of overruling the ACC and negatively correlated with the probability of not intervening. The selectivity correction term had a non-significant impact on the target speed decrement. The driver-specific error term has a significant effect on the magnitude of the target speed regulations, meaning that certain drivers choose larger ACC target speed regulations than others. The effect of this term did not differ significantly between target speed increments and decrements, meaning that drivers show a similar variability in increasing and decreasing the speed. Comparing the impact of the driver-specific error terms on the two levels of decision making reveals that drivers who have a smaller acceptable range with ACC active are more likely to resume manual control and to choose larger target speed regulations.

Table 5.5: Estimation results of the continuous-discrete choice model: ACC target speed regulation choice

Variable	Description	Parameters	Estimate	Robust t-stat.	Robust p-value
ACC target speed increase					
-	Mean ACC target speed increase	η^{TS+}	1.97	4.70	<0.005
NoviceADAS	Binary variable equal to 1 when the driver is inexperienced with ADAS	$\xi^{TS+}_{NoviceADAS}$	-0.518	-3.30	<0.005
C^{TS+}_{AAc}	Selectivity correction term in low risk situations	φ^{TS+}_{AAc}	1.44	2.45	0.01
C^{TS+}_{AL}	Selectivity correction term in low risk situations	φ^{TS+}_{AL}	-1.24	-2.24	0.02
ϑ_n	Individual-specific error term	γ^{TS}	0.355	2.20	0.03
υ^{TS+}_n	Observation-specific error term	ω^{TS+}	0.682	14.04	<0.005
ACC target speed decrease					
-	Mean ACC target speed decrease	η^{TS-}	1.86	6.63	<0.005
DiffTarSpeed	Difference between the ACC target speed and the speed of the subject vehicle in km/h	$\xi^{TS-}_{DiffTarSpeed}$	0.0240	3.49	<0.005
RelSpeed	Relative speed (leader speed – subject vehicle speed) in km/h	$\xi^{TS-}_{RelSpeed}$	-0.0299	-2.41	0.02
C^{TS-}_{I}	Selectivity correction term in high risk situations	φ^{TS-}_{I}	0.0301	0.19	0.85
ϑ_n	Individual-specific error term	γ^{TS}	0.355	2.20	0.03
υ^{TS-}_n	Observation-specific error term	ω^{TS-}	1.10	6.15	<0.005

Impact of the explanatory variables on the unconditional choice probabilities

To analyse the effect of variations in the explanatory variables on the unconditional ACC system state choice probabilities and on the magnitude of the ACC target speed regulations, we calculated the choice probability ratio and the target speed regulation ratio between a baseline observation and observations in which only one explanatory variable was altered while maintaining all the others fixed. In the baseline observation (choice probability ratio and target speed regulation ratio equal to 1), the driver had experience with ADAS and a score on the patient and careful driving style equal to the mean in this sample. The speed was equal to 87.2 km/h, the ACC target speed 102 km/h, the acceleration -0.0467 m/s^2, the distance headway 45.3 m, the relative speed -0.781 km/h, and the relative acceleration 0.0365 m/s^2. The ACC system had been activated for 94 s and the driver was not affected by cut-in manoeuvres, ramps, and exits. These values were selected based on the average situations in which control transitions and target speed regulations occurred. The unconditional ACC system state choice probabilities are influenced by the explanatory variables impacting the risk feeling and task difficulty evaluation and the ACC system state choices. The magnitude of the ACC target speed regulations is related to the variables influencing the ACC system state choices and the ACC target speed regulation.

The results for ratio variables are presented in Figure 5.3 and Figure 5.4, and for ordinal and nominal variables in Table 5.6. All findings support the previous interpretations. Figure 5.3 reveals that the time after activation, the acceleration (negative), and the driver specific error term are the variables that have a largest impact on the choice of overruling the system. The difference between the ACC target speed and the actual speed (negative) has the largest impact on the choice of increasing the ACC target speed. The relative speed (negative) and the relative acceleration (negative) have the strongest effect on the choice of deactivating the system. The relative speed (negative) has also the largest impact on the choice of decreasing the ACC target speed. In Table 5.6 the number of expected cut-ins during the next three seconds has the strongest effect on the probability of deactivations and target speed decrements. Figure 5.4 shows that the difference between the ACC target speed and the actual speed and the relative speed have the largest impact on the magnitude of the target speed decrement.

Table 5.6: Impact of the ordinal and nominal explanatory variables on the choice probability ratio (probability predicted divided by probability baseline observation) of transferring to Inactive (I), decreasing the ACC target speed (AS-), maintaining the ACC Active (A), increasing the ACC target speed (AS+), and transferring to Active and accelerate (AAc), and on the target speed regulation ratio (ACC target speed regulation predicted divided by ACC target speed regulation baseline observation) of decreasing (TS-) and increasing (TS+) the ACC target speed

Variables	I	AS-	A	AS+	AAc	TS-	TS+
AntCutIn3 = 1	3.981	3.981	0.9884	0.3373	1.438	1.000	0.8444
AntCutIn3 = 2	12.38	12.38	0.9427	0.0804	1.461	1.000	0.5557
AntCutIn3 = 3	30.41	30.41	0.8413	0.0110	0.8522	1.000	0.2613
OnRamp	2.648	0.7216	1.000	1.000	1.000	0.9822	1.0000
Exit	5.438	0.2499	1.000	1.000	1.000	0.9432	1.0000
Novice ADAS	1.000	1.000	1.000	1.000	1.000	1.000	0.5957

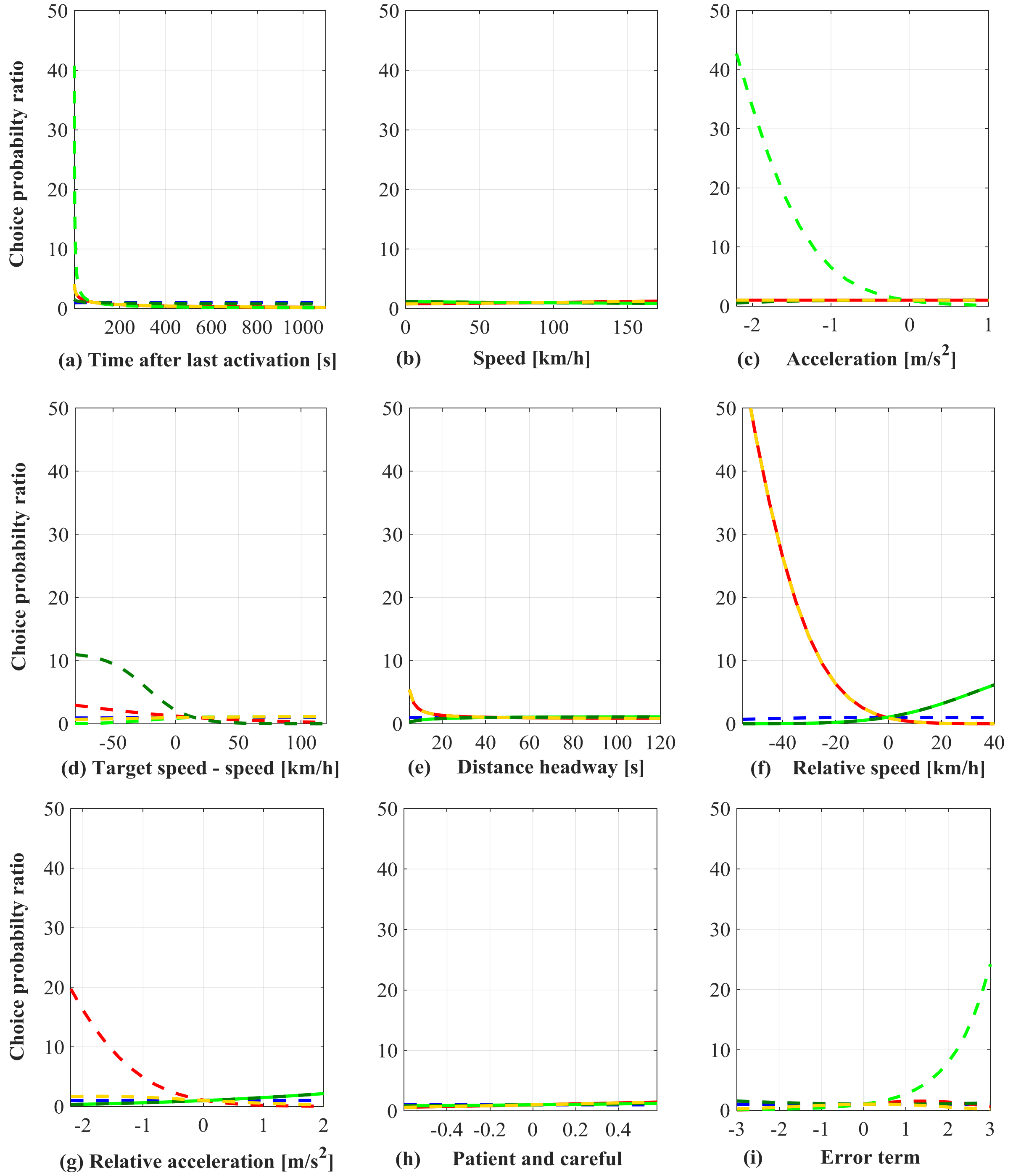

Figure 5.3: Impact of the explanatory variables and of the driver specific error terms on the choice probability ratio (probability predicted divided by probability baseline observation) of transferring to Inactive (red), decreasing the ACC target speed (orange), maintaining the ACC active (blue), increasing the ACC target speed (dark green), and transferring to Active and accelerate (light green). The variables are listed as follows: (a) time after last activation, (b) speed, (c) acceleration, (d) target speed – speed, (e) distance headway, (f) relative speed, (g) relative acceleration, (h) patient and careful driving style (centred on the mean value between drivers), and (i) driver specific error term.

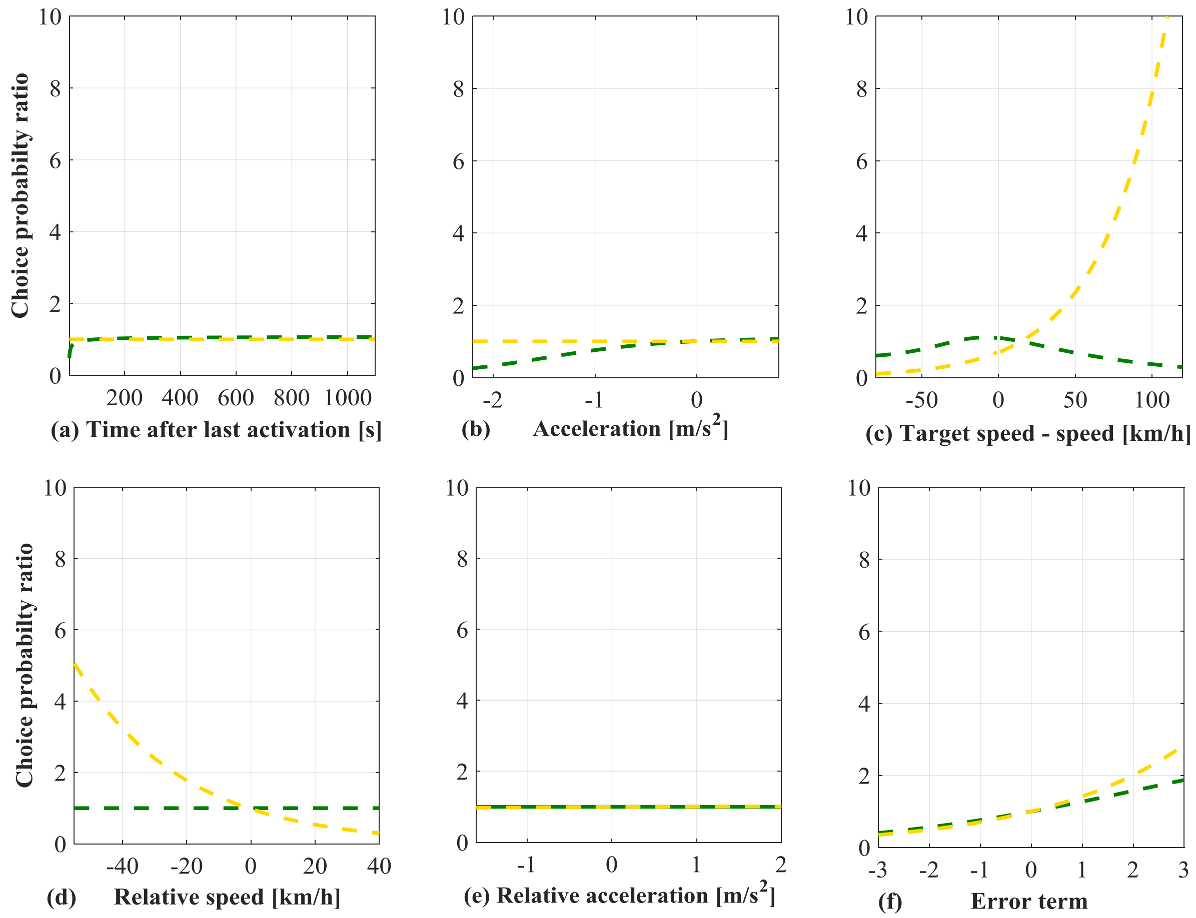

Figure 5.4: Impact of the explanatory variables and of the driver specific error term on the target speed regulation ratio (ACC target speed regulation predicted divided by ACC target speed regulation baseline observation) of decreasing (orange) and increasing (dark green) the ACC target speed. The variables are listed as follows: (a) time after last activation, (b) acceleration, (c) target speed – speed, (d) relative speed, (e) relative acceleration, and (f) driver specific error term.

5.6.4 Validation analysis

This section analyses the validity of the continuous-discrete choice model presented in Table 5.3-Table 5.5 compared to a choice model that has the same structure and includes only the constants. The aim is to understand the ability of the model to predict the choices of individual drivers on a different road segment and the choices of drivers not included in the estimation sample. The model should be applied to an independent dataset to understand its prediction capability. Since no similar independent datasets are available, two different approaches are proposed: the model is estimated on the observations of all drivers in two freeway segments and validated on the observations in the freeway segment excluded in the estimation phase (in-sample-out-of-time); the model is estimated on the observations of 80% of the drivers in the three freeway segments and validated on the observations of the drivers excluded in the estimation phase (out-of-sample-in-time).

To test out-of-time performances, the model was estimated on two freeway segments and validated on the freeway segment excluded in the estimation phase. The procedure was repeated for each freeway segment. To test out-of-sample performances, a five-fold cross validation approach was used due to the limited number of drivers available (Hastie et al., 2009). Drivers were assigned randomly to five groups, the model was estimated on four groups and validated on the group excluded in the estimation phase. The procedure was repeated five times. These approaches aimed to investigate differences between freeway segments and between drivers which were not captured in the model.

The model performances on the validation samples were assessed using three evaluation metrics: final log likelihood, area under the Receiver Operating Characteristic curve (AUC or AUROC), and Root Mean Square Error (RMSE). The final log likelihood allows determining which model has the highest capabilities in predicting the whole decision-making process (both ACC system state choices and target speed regulations). The multi-class AUC (Hand and Till, 2001) measures the pairwise discriminability of different system states in the discrete choice component of the model. The AUC was preferred to common evaluation metrics based on the confusion matrix (e.g., accuracy and precision) because it is insensitive to class skew and evaluates the model performances over different threshold values that can be used to forecast class membership (for a review on ROC analysis, refer to Fawcett (2006)). The RMSE measures the differences between the target speed regulations predicted by the regression models and the target speed regulations observed (prediction errors).

The final log likelihood, the AUC, and the RMSE of the model with constants only and of the continuous-discrete model on the validation samples are presented in Table 5.7 (in-sample-out-of-time) and in Table 5.8 (out-of-sample-in-time). The final log likelihood values indicate that the model proposed has higher forecasting accuracy than the model with constants only both in-sample-out-of-time and out-of-sample-in-time. The AUC shows that the choice component of the model has considerably higher discriminability capabilities than the choice model with constants only. The RMSE indicates that the regression models proposed have lower mean prediction errors than the regressions with constants only but result in larger errors on certain validation samples. Comparing the three freeway segments, one notes that the choice model shows a large accuracy improvement when it is validated on each segment while both regression models show a reduction in accuracy in the second freeway segment. This result means that, in the second segment, some drivers choose a small (or large) target speed regulation in situations in which the model predicts a large (or small) target speed regulation. This finding might be explained by different geometric characteristics or environmental conditions in the second freeway segment that were not captured by the explanatory variables. Comparing the five groups of drivers, one notes that the choice model shows a large accuracy improvement when it is validated on each group, while one of the regression models shows a reduction in accuracy when it is validated on groups 2, 3, and 4. This means that certain drivers in these groups showed a different behaviour in regulating the target speed than the others. Although further analysis is needed to investigate the origin of these differences, we conclude that the continuous-discrete model estimated is useful to predict the decision-making process of individual drivers on a different freeway segment and of drivers not included in the estimation sample.

Table 5.7: Validation analysis of the continuous-discrete choice model: two freeway segments versus one freeway segment (in-sample-out-of-time)

	2nd, 3rd seg. vs. 1st seg.	*1st, 3rd seg. vs. 2nd seg.*	*1st, 2nd seg. vs. 3rd seg.*	*M*	*SD*
Drivers	23	23	23	23	0
Observations	7598	7344	8626	7856	678.83
$L(c)$	-1371	-1176	-1063	-1195	167.46
$L(\hat{\beta})$	-1235	-1038	-975	-1091	132.15
$\frac{L(c)-L(\hat{\beta})}{L(c)}$	0.0995	0.0963	0.0606	0.0855	0.0216
$AUC_{tot}(c)$	0.5000	0.5000	0.5000	0.5000	0.0000
$AUC_{tot}(\hat{\beta})$	0.7563	0.7975	0.7688	0.7742	0.0211
$RMSE_{TS+}(c)$	0.8428	0.7688	0.7644	0.7920	0.0440
$RMSE_{TS+}(\hat{\beta})$	0.7981	0.7990	0.7324	0.7765	0.0382
$\frac{RMSE_{TS+}(c)-RMSE_{TS+}(\hat{\beta})}{RMSE_{TS+}(c)}$	0.0530	-0.0393	0.0418	0.0185	0.0504
$RMSE_{TS-}(c)$	0.7729	0.9613	1.7979	1.1774	0.5456
$RMSE_{TS-}(\hat{\beta})$	0.7175	1.0053	1.8306	1.1845	0.5778
$\frac{RMSE_{TS-}(c)-RMSE_{TS-}(\hat{\beta})}{RMSE_{TS-}(c)}$	0.0717	-0.0457	-0.0182	0.0026	0.0614

Note: *c* denotes the model with constants only, $\hat{\boldsymbol{\beta}}$ the continuous-discrete choice model.

Table 5.8: Validation analysis of the continuous-discrete choice model: 80% of drivers versus 20% of drivers (out-of-sample-in-time)

	G2-5 vs. G1	*G1, 3-5 vs. G2*	*G1-2, 4-5 vs. G3*	*G1-3, 5 vs. G4*	*G1-4 vs. G5*	*M*	*SD*
Drivers	5	4	5	4	5	4.6	0.55
Observations	4742	4687	4658	4758	4723	4714	40.82
$L(c)$	-818	-622	-679	-651	-749	-704	79.45
$L(\hat{\beta})$	-734	-564	-589	-590	-681	-632	72.64
$\frac{L(c)-L(\hat{\beta})}{L(c)}$	0.1027	0.0939	0.1333	0.0924	0.0910	0.1027	0.0177
$AUC_{tot}(c)$	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0
$AUC_{tot}(\hat{\beta})$	0.7688	0.7707	0.8204	0.7799	0.7693	0.7818	0.0197
$RMSE_{TS+}(c)$	1.1163	0.6451	0.7374	0.7925	0.7236	0.8030	0.1636
$RMSE_{TS+}(\hat{\beta})$	1.0853	0.6651	0.7987	0.6804	0.5930	0.7645	0.1735
$\frac{RMSE_{TS+}(c)-RMSE_{TS+}(\hat{\beta})}{RMSE_{TS+}(c)}$	0.0278	-0.0311	-0.0831	0.1414	0.1804	0.0471	0.1001
$RMSE_{TS-}(c)$	1.4753	0.8393	0.7017	1.1174	1.4647	1.1197	0.3158
$RMSE_{TS-}(\hat{\beta})$	1.3555	0.6118	0.6306	1.4024	1.3579	1.0716	0.3682
$\frac{RMSE_{TS-}(c)-RMSE_{TS-}(\hat{\beta})}{RMSE_{TS-}(c)}$	0.0812	0.2711	0.1013	-0.2550	0.0729	0.0543	0.1709

Note: c denotes the model with constants only, $\hat{\beta}$ the continuous-discrete choice model, G the group of drivers.

5.7 Conclusions and future research

This study has proposed a comprehensive model framework explaining the underlying decision-making process of drivers at an operational level based on Risk Allostasis Theory (RAT) (Fuller, 2011). This framework represents one of the first attempts to develop a conceptual model explaining driver interaction with driver assistance systems based on theories developed in the field of driver psychology. Two levels of decision making describing both control transitions and target speed regulations with full-range ACC are proposed: risk feeling and task difficulty evaluation, and ACC system state and ACC target speed regulation choice. If the perceived risk feeling and task difficulty level is higher than the maximum value acceptable, the driver will choose to deactivate the system or to decrease the ACC target speed maintaining the system active. If the perceived risk feeling level is lower than the minimum value acceptable, the driver will choose to overrule the ACC by pressing the gas pedal, to increase the ACC target speed maintaining the system active, or not to intervene. Notably, this conceptual framework supports the specification and the estimation of mathematical models that capture interdependencies between decisions of control transitions and target speed regulations in full-range ACC.

The mathematical formulation proposed accommodates decisions on both discrete and continuous variables, modelling unobservable constructs and interdependencies between decisions in terms of causality, unobserved driver characteristics, and state dependency. The model explicitly recognizes the ordinal and discrete nature of the underlying risk feeling and task difficulty evaluation, capturing both observed and unobserved heterogeneity in the minimum and in the maximum risk acceptable. The magnitude of the ACC target speed regulation is chosen simultaneously to the system state and correlations between these two choices are captured explicitly. Causality is addressed by modelling the observable decisions (control transitions and target speed regulations) as conditional on the unobservable constructs (feeling of risk and task difficulty evaluation). This formulation allows choices to maintain the system active to arise from different levels of perceived risk (acceptable and low), capturing explicitly drivers' propensity not to intervene. Correlations among decisions made by an individual driver are captured by introducing driver-specific error terms in each level of decision making. State dependency is addressed by including the driver behaviour characteristics of the subject vehicle and of its direct leader as explanatory variables in the different levels. The model allows to investigate the impact of different explanatory variables on each level of decision making and to quantify the impact of changes in these variables on drivers' decisions to transfer control and to regulate the target speed. The model parameters can be rigorously estimated based on empirical data using maximum likelihood methods.

The findings in the case study support the hypothesis that feeling of risk and task difficulty are the main factors informing drivers' decisions to transfer control and to regulate the target speed in full-range ACC. The model was estimated using driver behaviour data collected in an on-road experiment. Transitions to Inactive (deactivations) and ACC target speed reductions occurred most often in high risk feeling and task difficulty situations (high speeds, short distance headways, slower leader, and cut-ins expected), while transitions to Active and accelerate (overruling actions by pressing the gas pedal) and target speed increments in low risk feeling and task difficulty situations (low speeds, large distance headways and faster leader). Control transitions and ACC target speed regulations can be interpreted as an attempt to decrease or increase the complexity of a traffic situation. Individual characteristics and the functioning of the system influenced drivers' decisions significantly. These factors should be accounted for when analysing the acceptability of a full-range ACC. Interestingly, sometimes drivers do not intervene in low risk feeling and task difficulty situations. This result might be explained by difficulties in perceiving changes in low risk feelings, which might be influenced by human factors such as errors, shifts in attention and distraction.

The principal implication of this study is that, to describe driver interaction with ACC, a conceptual model framework is needed that connects driver behaviour characteristics, driver characteristics, ACC system settings, and environmental factors. This conceptual framework can be formulated mathematically using discrete choice models, which are able to capture unobservable constructs and interdependencies between different decisions made by the same driver. Other advantages of discrete choice models are that the model structure can be selected based on insights from driver control theories, the parameters can be formally estimated, and the estimation results are directly interpretable.

The estimation results presented in the case study need to be interpreted with caution. The sample of participants was limited (23) and was not representative of the driver population in terms of gender, age, experience with ADAS, and employment status. It is advised that future studies are carried out with a larger sample of participants that is representative of the driver population. The results of the validation analysis suggest that, to increase the prediction accuracy of the model, future research should investigate more in-depth both driver characteristics and environmental conditions. Moreover, further analysis is needed to generalize the results, which are influenced by the characteristics of the ACC system, to other types of driving assistance systems.

Nonetheless, the results have important implications for developing new driving assistance systems that can adapt their settings based on different traffic situations and driver characteristics to prevent control transitions while guaranteeing safety and comfort. The model proposed can be implemented into these new systems to identify the situations in which drivers are likely to resume manual control. Accounting for a certain variability in drivers' decision making, the model can also be used to forecast the probability that drivers resume manual control based on the programmed response of the system. These findings contribute to the development of new driving assistance systems that are acceptable for drivers in a wider range of traffic situations (Bifulco et al., 2013; Goodrich and Boer, 2003).

The model proposed can be directly implemented into a microscopic traffic flow simulation to analyse the impact of ACC on traffic safety and traffic flow efficiency at different penetration rates accounting for drivers' interventions. Previous microscopic traffic simulation models have proposed deterministic decision rules for resuming manual control in ACC, which were not supported by current theories of driver behaviour and were not estimated based on empirical data. The possibility of regulating the longitudinal control task by adjusting the ACC target speed was ignored. These methodological limitations were addressed in the current study. The data collection method proposed (controlled on-road experiment) allows analysing driving behaviour with full-range ACC in real traffic, controlling for potentially confounding factors such as road design and traffic conditions. In addition, the driver characteristics collected using the questionnaires contributed to explain the observed behaviour. These findings can increase the realism and accuracy of current driver behaviour models.

Further research is recommended to focus on increasing the behavioural realism of the model framework proposed. The framework is generic and can be extended to accommodate other explanatory variables and unobservable constructs. Driver decisions can be influenced by factors such as congestion levels, time pressure, presence of vehicles in the nearby lanes, number of heavy vehicles, number of lanes available, and lane width. Physiological measurements capturing the workload and the stress level experienced by drivers can be integrated into the framework as indicators of the feeling of risk and task difficulty perceived. Driver state monitor systems (e.g., eye-tracking) can be used to investigate the origin of drivers' choices to maintain the ACC active and the current target speed in low risk situations. These measurements could be integrated into the choice model using, for instance, latent variable models (Vij and Walker, 2016; Walker, 2001). Similar model frameworks can be developed to investigate driver adaptations at an operational level to other driving assistance systems and to higher levels of vehicle automation. When the driver monitors the environment permanently (SAE Level 1 and 2), risk feeling is expected to be the main construct informing the decision-making process. When the driver is requested to monitor the environment only in specific traffic situations (SAE Level 3 and 4), new constructs such as driving comfort and engagement in non-driving tasks can be explored.

Chapter 6

Conclusions and recommendations

The first part of this dissertation presented empirical studies describing driver behaviour characteristics during control transitions between ACC and manual driving. The second part proposed mathematical models capturing drivers’ decisions to resume manual control.

This chapter discusses the main research findings, conclusions, implications for practice, limitations and directions for future research. The chapter is structured as follows. Section 6.1 summarizes the main findings, in terms of duration and magnitude of significant changes in driver behaviour characteristics during control transitions and factors influencing drivers’ decisions to resume manual control and to regulate the ACC target speed. Section 6.2 highlights the relevance of the methods and of the empirical results in this thesis for understanding and modelling driver behaviour with driving assistance systems. Section 6.3 describes the value of these findings for developing human-centred driving assistance systems and for predicting the impact of control transitions on traffic flow operations. Finally, Section 6.4 discusses the limitations of the findings in this thesis and directions for future research.

6.1 Main findings

The main objectives of this thesis were to gain empirical insights into driving behaviour during control transitions between full-range Adaptive Cruise Control (ACC) and manual driving, and to model drivers' decisions to resume manual control. This thesis addressed four main research questions as follows: (1) How do drivers behave when full-range ACC deactivates because of a sensor failure? (2) How do driver behaviour characteristics change over time after the driver deactivates the full-range ACC or overrules it by pressing the gas pedal? (3) What factors (driver behaviour, driver, and road characteristics) influence drivers' decisions to resume manual control in full-range ACC? (4) How to model drivers' decisions to resume manual control and to regulate the target speed in full-range ACC? The answers to these four research questions are summarized in this section.

6.1.1 Driver behaviour characteristics during control transitions between full-range Adaptive Cruise Control and manual driving: a driving simulator experiment

Driver behaviour during control transitions between ACC and manual driving has been analysed in both driving simulator and Field Operational Test (FOT) studies. Most driving simulator studies have been conducted in the field of human factors and have focused on drivers' reaction times when resuming manual control after automation failures. Findings in these studies cannot be easily generalized to real traffic situations due to the oversimplified driving scenarios and a sample of participants that do not represent the driving population. FOTs were conducted in the field of traffic engineering with ACC systems inactive at low speeds. In these studies, potential confounding factors such as road design and traffic conditions cannot be precisely controlled for. Therefore, limited insight was gained on the influence of control transitions on the longitudinal driver behaviour characteristics.

Chapter 2 proposed a driver simulator experiment to acquire driver behaviour data with a high degree of controllability and analyse the influence of control transitions between full-range ACC and manual driving on speed, acceleration, and time headway. Sixty-seven participants were assigned to one of three conditions randomly and successfully completed the experiment. In the baseline condition, participants drove manually. In the first experimental condition, a sensor failure was simulated at a specific location where the vehicle decelerated, and drivers were expected to resume manual control. In the second experimental condition, drivers activated and deactivated the ACC by pressing a button whenever they desired.

Statistical tests indicated that the distributions of speed, acceleration and time headway significantly differed between the three conditions. After the sensor failure, the median time to resume manual control was equal to 3.85 s and the corresponding speed variation was -18.18 km/h (AIDC transition). After the sensors were functioning again, the median time before re-activating the ACC was equal to 5.80 s and the corresponding speed variation was -4.22 km/h (DIAC transition). Small mean time headways (1.30 s) were observed in the freeway segment where ACC was activated permanently, while higher mean values (2.10 s) were found in the segment where the sensor failure was simulated, and control transitions were possible. These results seem to be consistent with previous findings and suggest that control transitions between ACC and manual driving may influence significantly the longitudinal driver behaviour characteristics, potentially reducing the expected benefits of ACC on traffic flow efficiency.

6.1.2 Driver behaviour characteristics during control transitions from full-range Adaptive Cruise Control to manual driving: an on-road experiment

FOTs have showed that the mean driver behaviour characteristics (values aggregated over 10-s intervals) change significantly after drivers deactivate ACC systems that are inactive at low speeds. However, these studies disregarded any temporal evolution of the driver behaviour characteristics over the 10-s intervals and did not control for the confounding effect of any additional control transitions initiated within these time intervals. Variations in the mean driver behaviour characteristics in medium-dense traffic flow conditions, which are more relevant to traffic operations, were not analysed explicitly. Therefore, the impact of these control transitions between ACC and manual driving on the driver behaviour characteristics was still unclear.

Chapter 3 proposed an on-road experiment to analyse the influence of control transitions from full-range ACC to manual driving (DIDC) on speed, acceleration, distance headway, and relative speed. Twenty-three participants drove a research vehicle equipped with full-range ACC on a 35.5 km freeway in Munich during peak hours. This data collection method allows controlling for potentially confounding factors such as road design and traffic conditions, which are common limitations of FOTs and naturalistic studies.

Linear mixed-effects models were estimated to identify statistically significant changes in the driver behaviour characteristics over time a few seconds after manual control was resumed (transition period). The results revealed that the time period after deactivation, the traffic density and the system state (Inactive, Active, and Active and accelerate) had a significant impact on the driver behaviour characteristics. At high densities, the speed decreased significantly by 10.5 km/h (from 44.4 to 33.9 km/h) in 4 s after the ACC system was deactivated and it increased significantly by 6.50 km/h (from 37.3 to 44.7 km/h) in 5 s after the system was overruled by pressing the gas pedal. These speed reductions (or increments) can be interpreted as a compensation strategy to decrease (or increase) the feeling of risk and task difficulty perceived. The findings are useful for the development of driving assistance systems that are acceptable for drivers in a wider range of traffic situations and for the development of microscopic traffic flow models that mimic drivers' response during control transitions.

6.1.3 Factors influencing drivers' decisions to resume manual control in full-range ACC

FOTs have found that drivers may prefer to deactivate ACC in dense traffic flow conditions and before changing lanes. Results in Chapter 2 indicated that drivers may differ in their choices to activate and to deactivate the ACC system in similar traffic situations. However, most of the models currently used to evaluate the impact of ACC on traffic flow do not account for control transitions. A few mathematical models have proposed deterministic decision rules for transferring control, ignoring heterogeneity between and within drivers in the decision-making process.

Chapter 4 analysed the main factors that influence drivers' decisions to resume manual control in full-range ACC in a mixed logit model. The dataset was collected in the controlled on-road experiment described in Chapter 3. The results revealed that drivers were more likely to deactivate the ACC and resume manual control when approaching a slower leader, when expecting nearby vehicles cutting in, when driving above the ACC target speed, and before exiting the freeway. Drivers were more likely to overrule the ACC system by pressing the gas pedal a few seconds after the system has been activated, and when the vehicle decelerated. Everything else being equal, some drivers had higher probabilities to resume manual control. These findings suggest that a novel conceptual framework linking ACC system settings, driver behaviour characteristics, driver characteristics, and environmental factors is needed to model driver behaviour during control transitions between ACC and manual driving.

6.1.4 Modelling decisions of control transitions and target speed regulations in full-range ACC based on Risk Allostasis Theory

Few studies have estimated the probability that drivers resume manual control in ACC based on empirical data. Results in Chapter 4 have shown that drivers were likely to deactivate full-range ACC when approaching a slower leader and to overrule it by pressing the gas pedal a few seconds after the system has been activated. Everything else being equal, some drivers were more likely to resume manual control than others. Drivers can adapt the ACC target speed to regulate the longitudinal control task, and this possibility can influence their decision to resume manual control. However, a theoretical framework explaining driver decisions to transfer control and to regulate the target speed in full-range ACC was missing.

Chapter 5 developed a modelling framework describing the underlying decision-making process of drivers with full-range ACC at an operational level, grounded on Risk Allostasis Theory. Based on this theory, a driver will choose to resume manual control or to regulate the ACC target speed if its perceived level of risk feeling and task difficulty falls outside the range considered acceptable to maintain the system active. The feeling of risk and task difficulty evaluation was formulated as a generalized ordered probit model with random thresholds, which varied between drivers and within drivers over time. The ACC system state choices were formulated as logit models and the ACC target speed regulations as regression models, in which correlations between system state choices and target speed regulations were captured explicitly. This continuous-discrete choice model framework was able to address interdependencies across drivers' decisions in terms of causality, unobserved driver characteristics, and state dependency, and to capture inconsistencies in drivers' decision making that might be caused by human factors.

The model was estimated using the dataset collected in the on-road experiment with full-range ACC described in Chapter 3. The results revealed that the perceived level of risk feeling and task difficulty was higher when speeds were higher and distance headways were shorter, when approaching a slower leader and when expecting vehicles cutting in. Everything else being equal, some drivers were more likely to overrule the system by pressing the gas pedal. The model can be used to forecast driver response to a driving assistance system that adapts its settings to prevent control transitions in non-safety critical situations. The model can also be implemented into a microscopic simulation to assess the effects of ACC on traffic flow efficiency accounting for control transitions and target speed regulations.

6.2 Conclusions

The choice model predicting control transitions and target speed regulations in full-range ACC is generic and implementable into microscopic traffic flow models. To the best of the author's knowledge, this is the first model predicting both transitions to manual control and target speed regulations in full-range ACC in a wide range of traffic situations. The model proposed can be directly estimated based on empirical data. Since the model framework is generic, it can be applied to predict driver's decision making at an operational level with other advanced driving assistance systems (ADAS). The model can be implemented into a microscopic simulation to assess the impacts of ACC on traffic flow efficiency and safety accounting for control transitions and target speed regulations. The model can also be implemented into an ADAS to identify the situations in which drivers are likely to resume manual control.

Drivers' decisions to resume manual control and to regulate the target speed in full-range ACC can be interpreted based on Risk Allostasis Theory (RAT). This is one of the first attempts to develop a model framework explaining driver interaction with ADAS at an operational level based on theories developed in the field of driver psychology. The interpretation proposed is supported by the empirical findings in the choice models and by the analysis of the mean driver behaviour characteristics after manual control is resumed. The RAT contributes to shed light on the decision-making process of drivers. These findings point towards the importance of incorporating realistic driver behaviour mechanisms in driver behaviour models.

When the full-range ACC is active, drivers choose to resume manual control or regulate the target speed based on the driver behaviour characteristics, the system settings, personal characteristics, and environmental conditions. This thesis provides one of the first comprehensive assessments of the main factors influencing drivers' decisions with full-range ACC based data collected in an on-road experiment. Drivers are more likely to deactivate the full-range ACC or reduce the target speed when approaching a slower leader and when expecting vehicles cutting-in. Drivers are more likely to overrule the system by pressing the gas pedal or increase the target speed a few seconds after the activation, when the vehicle decelerates, and when approaching a faster leader. Everything else being equal, some drivers are more likely to overrule the system by pressing the gas pedal. To predict driver interaction with the ACC system, all these factors should be accounted for.

Control transitions from full-range ACC to manual driving influence significantly the driver behaviour characteristics for a few seconds after manual control is resumed. To the best of the author's knowledge, this is one of the first studies capturing explicitly the duration of the transition period and the magnitude of the corresponding variation in driver behaviour characteristics after drivers deactivated or overruled the ACC based on data collected in an on-road experiment. The speed decreased significantly after the driver deactivated the system and it increased significantly after the driver overruled the system by pressing the gas pedal in each traffic condition. This is also one of the first studies that analyse driver behaviour characteristics during control transitions and the time needed by drivers to re-activate the system after a sensor failure in a driving simulator experiment with a high degree of controllability. The speed decreased after the sensor failure in light traffic conditions because drivers needed a certain time period to react and respond by pressing the gas pedal. From a behavioural point of view, these speed reductions (or increments) can be interpreted as a compensation strategy to decrease (or increase) the feeling of risk and task difficulty, and the time interval associated as the duration needed to stabilize driving behaviour after manual control is resumed (transition period).

6.3 Implications for practice

The data collection and data analysis methods proposed in this thesis are useful to model behavioural adaptations for different classes of road users based on empirical data. The findings are relevant to researchers, industries and policy-makers interested in developing new ADAS and in evaluating their impacts on traffic operations. This section discusses the practical implications of the findings in this thesis for developing ADAS that are acceptable for drivers in a wider range of traffic situations, and for predicting the impact of different penetration rates of full-range ACC vehicles on traffic flow efficiency and safety.

Full-range ACC systems that mimic human driving style as described by the empirical findings in this thesis are needed to enhance comfort and acceptability. The results suggest the controllers of human-like ACC systems should be designed based on the driver behaviour characteristics of the subject vehicle and its direct leader, on the driver characteristics, and on environmental conditions. It is also advised that these controllers could be calibrated by driving for a short period of time to adapt the parameters to different driving styles and road environments. The choice model based on feeling of risk and task difficulty can be directly implemented into the system to identify the situations in which drivers are likely to resume manual control. In these situations, the system can be programmed to anticipate driver response in order to prevent transitions to manual control. Drivers would maintain the ACC active if the system decreased the speed, while guaranteeing safety and comfort, in traffic situations in which they are likely to deactivate. Similarly, drivers would maintain the ACC active if the system increased the speed in situations in which they are likely to overrule by pressing the gas pedal. A controller based on these empirical findings is expected to be acceptable for drivers in a wider range of traffic situations, increasing the market penetration and the actual adoption of the system.

Microscopic traffic flow models that capture the empirical findings in this thesis are needed to assess accurately the impacts of full-range ACC on traffic flow efficiency and safety. The results have shown that there are large differences between and within drivers in the same traffic situation, which can be explained by the functioning of the system, observed and unobserved driver characteristics, and environmental conditions. All these factors should be included into microscopic traffic flow models. The choice model proposed in this thesis can be directly implemented into a microscopic simulation package and is expected to result in more accurate predictions than the models available, which are based on deterministic decision rules. In addition, a car-following model grounded on feeling of risk and task difficulty can be developed to capture explicitly adaptations in driver behaviour characteristics during control transitions. In this model, the vehicle acceleration can be specified explicitly as a function of two additive terms, the first one representing regular car-following behaviour and the second one representing adaptations during control transitions (similar to the advanced car-following models capturing compensation effects at sags by Goni-Ros et al. (2016), and capturing driver distraction by Hoogendoorn et al. (2013) and by Saifuzzaman et al. (2015)). For instance, the second term can be specified as a function of the transition period and the corresponding speed change described in this thesis. Implementing this advanced car-following model into a microscopic traffic flow simulation, the impact of transitions from ACC to manual control on capacity, capacity drop and string stability can be investigated more realistically than in current traffic flow simulations.

6.4 Recommendations for future research

The findings in this thesis are subject to certain limitations, which are related to the data collection method, the experimental design, the sample of participants, and the characteristics of the full-range ACC systems tested. Future research can address the shortcomings of these experimental designs, explore the impact of other factors on driver behaviour, and extend the analysis to situations in which lane changes are executed. Limitations and directions for future research are discussed in this section.

Drivers' performances might be biased by the controlled nature of the driving simulator and of the on-road experiments, in which an observer was present. The empirical findings in both experiments cannot be directly generalised to other types of driving assistance systems. In the driving simulator experiment, the simplified driving scenarios and the virtual environment could result in a reduction in validity. The ACC system settings (target speed and time headway) could not be regulated when the system was active. Participants drove for a short period of time (8-20 minutes) and because of this, limited insight was gained on the variations within drivers over time. The findings are related to light traffic flow conditions and cannot be directly extended to dense traffic flow. The on-road experiment addressed most of these limitations. In the on-road experiment, however, sensor failures and TOR in safety critical situations were not explicitly tested due to ethical considerations. The number of automation-initiated control transitions (AIDC) that occurred was too limited for statistical analyses. AIDC transitions can be further analysed in large naturalistic driving studies and in on-road studies designed to guarantee the safety of participants in these situations. In addition, the experiment consisted of a single drive along a pre-set test road and a baseline condition in manual driving was not available. The sample of participants (23 drivers) was relatively small, so limited insight was gained into the variations between drivers. Due to insurance constraints, participants were recruited among the BMW employees in Munich (Germany) and are not representative of the driver population in terms of gender, age, employment status and experience with ADAS. It is advised that future studies are carried out with a larger sample of participants which is representative of the driver population.

The data analysis methods proposed in this study are useful to explore the impact of relevant explanatory factors on driver behaviour in control transitions. The linear mixed-effects models can be used to investigate the impact of other factors, such as lane changes, driver characteristics (e.g., experience with the ACC system and driving styles), and characteristics of the freeway segment, on adaptations in driver behaviour characteristics. The analysis can be extended to lateral driver behaviour characteristics. Physiological measurements capturing driver workload and situation awareness can be analysed to shed light on the origin of these adaptations (De Winter et al., 2014). However, the linear mixed-effects models developed could only capture few other factors simultaneously with the interaction of time (20 levels), due to the number of observations available. The choice model can be used to investigate the impact of other explanatory variables, such as congestion levels, time pressure, presence of vehicles in the nearby lanes, number of heavy vehicles, number of lanes available and lane width, on feeling of risk and task difficulty evaluations. The analysis can be extended to situations in which drivers execute lane changes. In these situations, drivers might be influenced in their decisions by other factors, such as the gaps available and the speeds of the vehicles in the nearby lanes. To increase the realism of the current model, physiological measurements capturing the workload and the stress level experienced by drivers can be integrated into the framework as indicators of the feeling of risk and task difficulty perceived.

Driver state monitor systems (e.g., eye-tracking) can be used to investigate the origin of drivers' choices to maintain the ACC active and the current target speed in low risk situations.

Similar linear mixed-effects models and choice models can be developed to investigate driver adaptations at an operational level to other driving assistance systems and to higher levels of vehicle automation. Adaptation effects are expected to increase for higher levels of automation, when the system controls both the lateral and the longitudinal control task (SAE Levels 2-4) and drivers are requested to monitor the environment only in specific situations (SAE Level 3-4). When the driver monitors the environment permanently (SAE Level 1-2), risk feeling is expected to be the main construct influencing the decision-making process. When the driver is requested to monitor the environment only in specific traffic situations (SAE Level 3-4), new constructs such as driving comfort and engagement in non-driving tasks can be explored.

Future research can focus on assessing the performances of current car-following and lane changing models during control transitions between automation and manual driving. Novel car-following models based on driver control theories can be developed to describe driver behaviour during control transitions as discussed in Section 6.3. Finally, these new mathematical models could be implemented into a microscopic simulation to investigate the impacts of control transitions on traffic flow efficiency and safety.

Appendix A. Validation analysis

This section analyses the validity of the mixed logit model presented in Table 4.7 compared to a logit model that includes only the constants. The aim is to understand the ability of the model to predict the choices of individual drivers on a different road segment and the choices of drivers not included in the estimation sample. The validation analysis was carried out as described in Section 5.6.4. The model was estimated based on part of the observations and validated based on the observations excluded in the estimation sample.

The final log likelihood values of the model with constant only and of the mixed logit model on the validation samples are presented in Table A.1 (in-sample-out-of-time) and Table A.2 (out-of-sample-in-time). Notably, the model proposed has higher forecasting accuracy than the model with constants only both in-sample-out-of-time and out-of-sample-in-time. Comparing the three freeway segments reveals that the choice model shows a large accuracy improvement when it is validated on each segment. Comparing the five groups of drivers reveals that the smallest accuracy improvements occur when the model is validated on group 4. This means that certain drivers in this group showed a different behaviour than the others. Although further analysis is needed to investigate the origin of these differences, this validation analysis shows that the mixed logit model is useful to predict the decision-making process of individual drivers on a different freeway segment and of drivers not included in the estimation sample.

Table A.1: Validation analysis of the mixed logit model: two freeway segments versus one freeway segment (in-sample-out-of-time)

	Drivers	Obs.	Constant log likelihood $L(c)$	Final log likelihood $L(\hat{\beta})$	$\frac{L(c)-L(\hat{\beta})}{L(c)}$
2^{nd}, 3^{rd} seg. vs. 1^{st} seg.	23	7598	-405	-338	0.1668
1^{st}, 3^{rd} seg. vs. 2^{nd} seg.	23	7344	-324	-248	0.2369
1^{st}, 2^{nd} seg. vs. 3^{rd} seg.	23	8626	-341	-274	0.1958
M	23	7856	-357	-286	0.1998
SD	0	678.83	42.79	46.34	0.0352

Table A.2: Validation analysis of the mixed logit model: 80% of drivers versus 20% of drivers (out-of-sample-in-time)

	Drivers	Obs.	Constant log likelihood $L(c)$	Final log likelihood $L(\hat{\beta})$	$\frac{L(c)-L(\hat{\beta})}{L(c)}$
Groups 2-5 vs. group 1	5	4742	-291	-219	0.2473
Groups 1, 3-5 vs. group 2	4	4687	-184	-143	0.2220
Groups 1-2, 4-5 vs. group 3	5	4658	-175	-136	0.2186
Groups 1-3, 5 vs. group 4	4	4758	-235	-220	0.0656
Groups 1-4 vs. group 5	5	4723	-186	-147	0.2088
M	4.60	4714	-214	-173	0.1924
SD	0.55	40.82	48.96	42.36	0.0723

Appendix B. Data analysis

This appendix provides the analysis of the driver characteristics and of the driver behaviour characteristics when drivers resume manual control in full-range ACC and regulate the ACC target speed.

Table B.1: Two sample Kolmogorov-Smirnov test (p-value) of the driver behaviour characteristics when drivers transfer the ACC to Inactive (I), decrease the ACC target speed (AS-), maintain the ACC Active (A), increase the ACC target speed (AS+), and transfer to Active and accelerate (AAc)

Variables	I vs. AS-	I vs. A	I vs. AAc	AS- vs. A
Time after last activation	0.254 (**)	$4.10 \cdot 10^{-5}$	$8.64 \cdot 10^{-5}$	0.000354
Speed	0.320 (**)	0.00107	0.0486 (*)	$1.16 \cdot 10^{-5}$
Acceleration	0.438 (**)	0.428 (**)	0.00320	0.000546
Target time headway – time headway	0.900 (**)	0.185 (**)	0.000110	0.00149
Target speed – speed	0.613 (**)	0.228 (**)	0.464 (**)	0.00214
Distance headway	0.781 (**)	0.00837	0.0335 (*)	$1.69 \cdot 10^{-8}$
Relative speed	0.0680 (**)	$2.83 \cdot 10^{-8}$	0.000230	$3.26 \cdot 10^{-5}$
Relative acceleration	0.000485	$1.17 \cdot 10^{-8}$	$7.67 \cdot 10^{-9}$	0.0694 (**)

Variables	AS- vs. AS+	AS+ vs. A	AS+ vs. AAc	AAc vs. A
Time after last activation	0.301 (**)	$4.10 \cdot 10^{-6}$	$3.04 \cdot 10^{-10}$	$5.78 \cdot 10^{-27}$
Speed	0.000212	$3.02 \cdot 10^{-7}$	0.0182 (*)	$4.27 \cdot 10^{-5}$
Acceleration	$2.43 \cdot 10^{-5}$	0.00189	$5.70 \cdot 10^{-13}$	$2.19 \cdot 10^{-10}$
Target time headway – time headway	0.424 (**)	$2.01 \cdot 10^{-8}$	0.0905 (**)	$1.74 \cdot 10^{-11}$
Target speed – speed	$3.36 \cdot 10^{-5}$	$8.66 \cdot 10^{-29}$	$5.99 \cdot 10^{-9}$	0.00496
Distance headway	0.121 (**)	$3.69 \cdot 10^{-8}$	$1.17 \cdot 10^{-6}$	0.128 (**)
Relative speed	$1.94 \cdot 10^{-10}$	$1.34 \cdot 10^{-17}$	$1.30 \cdot 10^{-8}$	0.0952 (**)
Relative acceleration	0.0296 (*)	0.000271	0.0626 (**)	0.00108

Note: (**) p-value>0.05; (*) 0.01<p-value<0.05.

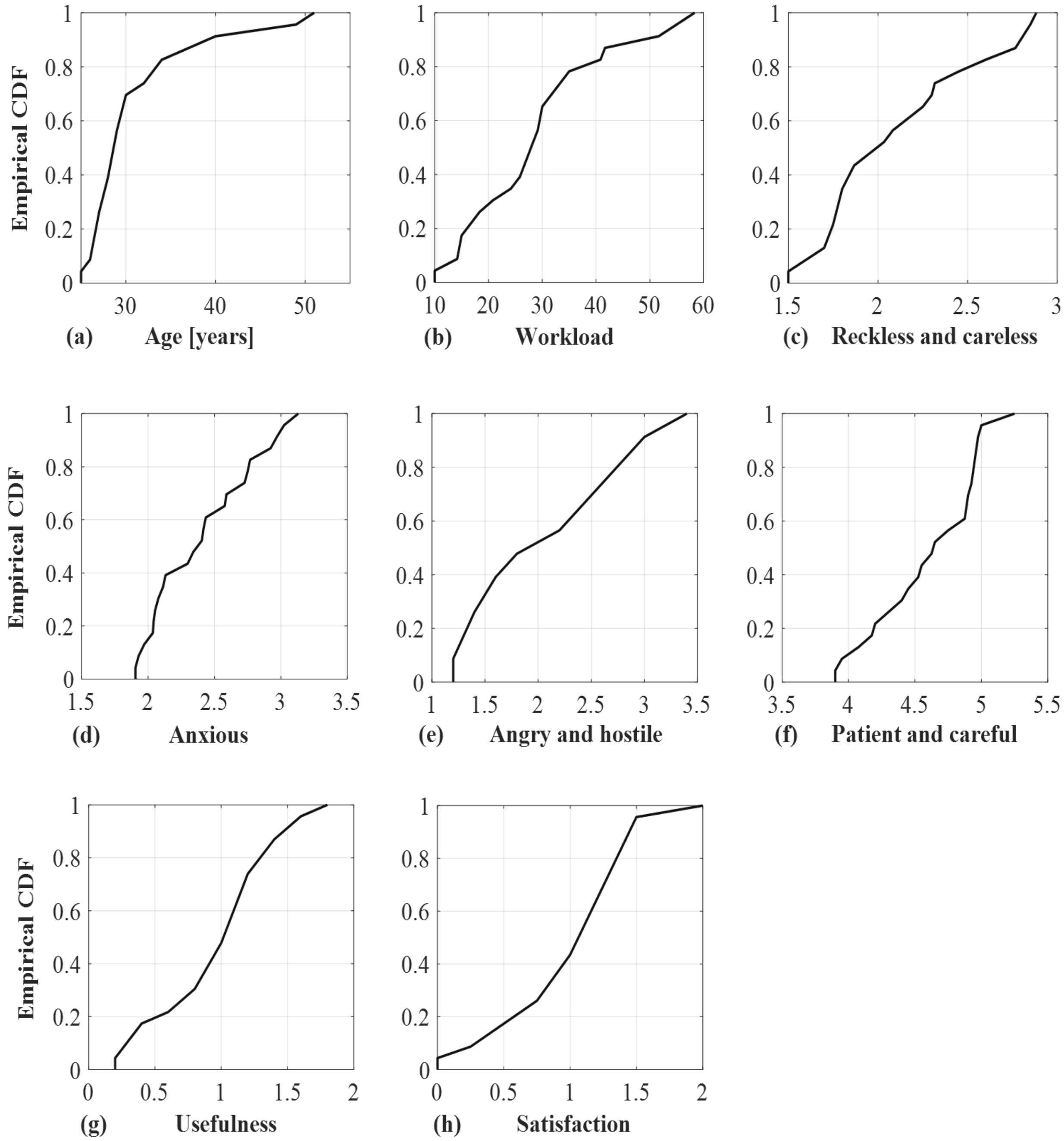

Figure B.1: Empirical cumulative distribution functions of the driver characteristics (continuous variables): (a) age, (b) workload (Byers et al., 1989; Kyriakidis et al., 2014), (c) reckless and careless driving style, (d) anxious driving style, (e) angry and hostile driving style, (f) patient and careful driving style (Taubman-Ben-Ari et al., 2004), (g) usefulness, and (h) satisfaction (Kyriakidis et al., 2014; Van der Laan et al., 1997). The workload is scored on a scale from 0 to 100, the driving styles on a scale from 1 to 6, and usefulness and satisfaction on a scale from -2 to 2.

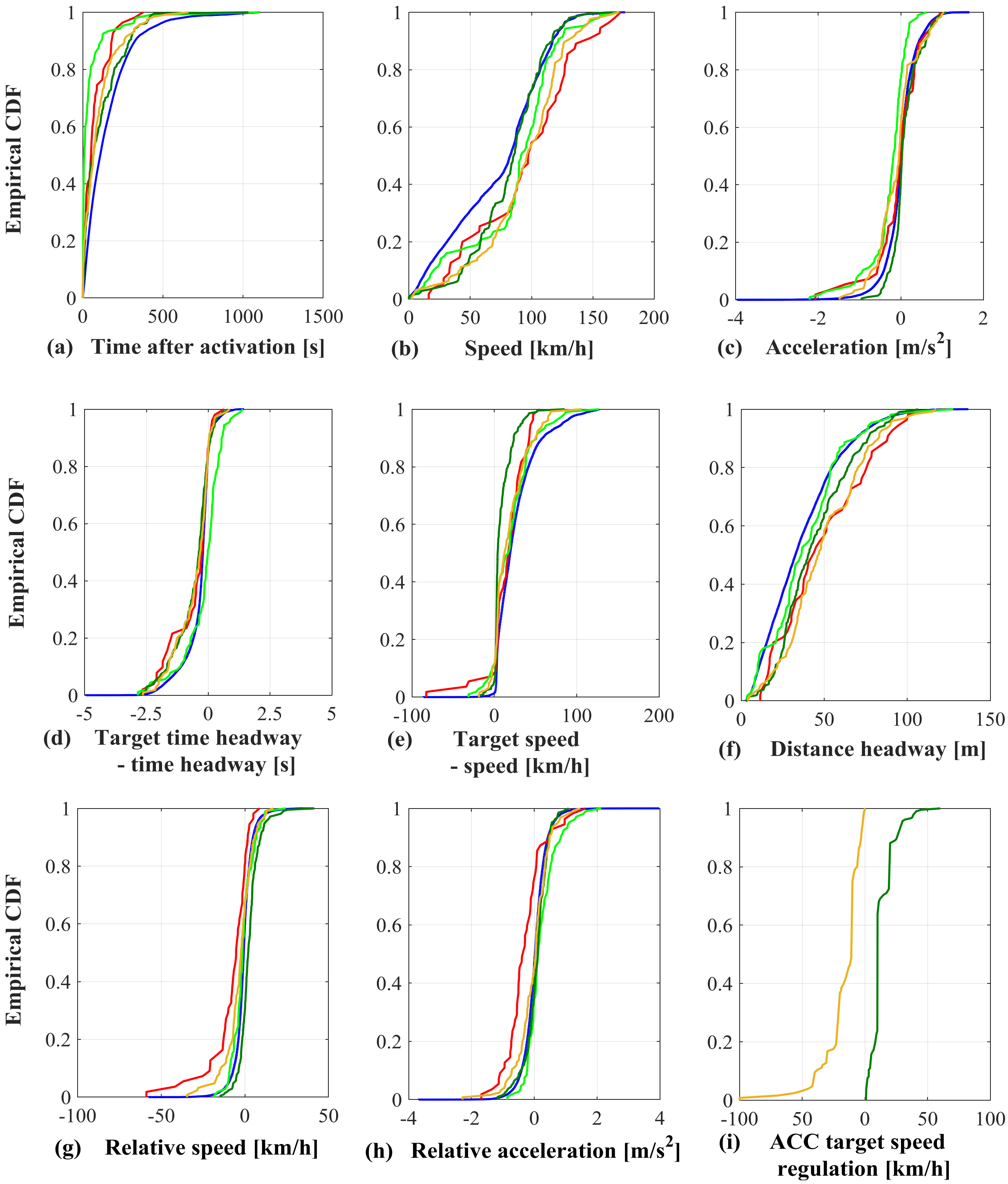

Figure B.2: Empirical cumulative distribution functions of the driver behaviour characteristics of transferring to Inactive (red), decreasing the ACC target speed (orange), maintaining the ACC active (blue), increasing the ACC target speed (dark green), and transferring to Active and accelerate (light green). The variables are listed as follows: (a) time after last activation, (b) speed, (c) acceleration, (d) target time headway – time headway, (e) target speed – speed, (f) distance headway, (g) relative speed, (h) relative acceleration, and (i) ACC target speed regulation.

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Summary

Chapter 1 Introduction

Automated vehicles and advanced driving assistance systems are expected to reduce congestion, accidents, and levels of emissions. Automated vehicles, in particular those that can show cooperative behaviour, may increase roadway capacity, improve traffic flow stability, and speed up the outflow from a queue. Automated vehicles are expected to mitigate traffic accidents by reducing driver error, which is responsible for a large proportion of collisions. The first step towards understanding the impact of automated vehicles on road traffic is to investigate currently available systems such as Adaptive Cruise Control (ACC). ACC assists drivers in maintaining a target speed and time headway and therefore has a direct effect on the longitudinal control task.

Field Operational Tests (FOTs) have shown that drivers might prefer to deactivate ACC systems which are inactive at low speeds in dense traffic flow conditions and before changing lanes. In addition, drivers might be forced to deactivate the system because of its operational limitations or a sensor failure. These transitions between automated and manual driving are called *control transitions* and can have an impact on traffic flow efficiency and safety. The circumstances in which these transitions occur are related to the characteristics of the driver support system, the drivers themselves, the road, and the traffic flow.

Despite the potential effects on traffic operations, most car-following and lane-changing models currently used to evaluate the impact of ACC do not describe control transitions. A few mathematical models have proposed deterministic decision rules for transferring control and have ignored possible changes in manual driving behaviour before the system is activated and after the system is deactivated. To date, limited efforts have been made to study and model control transitions between full-range ACC and manual driving in a way that would be suitable for implementation into microscopic traffic simulation models. The main *challenges* in this direction include (1) designing driving simulator and on-road experiments to better understand driver behaviour during control transitions, (2) analysing adaptations in driver behaviour characteristics when drivers resume manual control, and (3) developing a modelling framework based on theories of driver psychology to predict drivers' choices to transfer control.

The main *objectives* of this thesis were (1) to gain empirical insights into driving behaviour during these control transitions (Challenge 2) and (2) to model drivers' decisions to resume manual control (Challenge 3). To achieve these objectives, empirical data were collected in driver simulator and on-road experiments (Challenge 1). To gain insights into adaptations in driver behaviour characteristics during control transitions (Objective 1), this thesis addressed two main *research questions* as follows: (1) How do drivers behave when full-range ACC deactivates because of a sensor failure (Chapter 2)? (2) How do driver behaviour characteristics change over time after the driver deactivates the full-range ACC or overrules it by pressing the gas pedal (Chapter 3)? To develop a model framework that predicts drivers' choices to transfer control and to regulate the ACC target speed (Objective 2), the following research questions were addressed: (3) What factors (driver behaviour, driver, and road characteristics) influence drivers' decisions to resume manual control in full-range ACC (Chapter 4)? (4) How to model drivers' decisions to resume manual control and to regulate the target speed in full-range ACC (Chapter 5)?

Chapter 2 Driver behaviour characteristics during control transitions between full-range ACC and manual driving: a driving simulator experiment

Driver behaviour during control transitions between ACC and manual driving has been analysed in both driving simulator and FOT studies. Most driving simulator studies have been conducted in the field of human factors and have focused on reaction times in automation failures. FOTs were conducted in the field of traffic engineering with ACC systems inactive at low speeds. However, an experiment investigating the impact of control transitions on the longitudinal driver behaviour characteristics with a high degree of controllability was missing.

This thesis analysed the influence of control transitions between full-range ACC and manual driving on speed, acceleration, and time headway based on data collected in a driver simulator experiment. Sixty-seven participants were assigned to one of three conditions randomly and successfully completed the experiment. In the baseline condition, participants drove manually. In the first experimental condition, a sensor failure was simulated at a specific location where the vehicle decelerated and drivers were expected to resume manual control. In the second experimental condition, drivers activated and deactivated the ACC pressing a button whenever they desired.

Statistical tests indicated that the distributions of speed, acceleration and time headway significantly differed between the three conditions. In the first experimental condition, the speed dropped after the sensor failure (Figure I.A). These results seem to be consistent with previous findings and suggest that control transitions between ACC and manual driving may influence significantly the longitudinal driver behaviour characteristics.

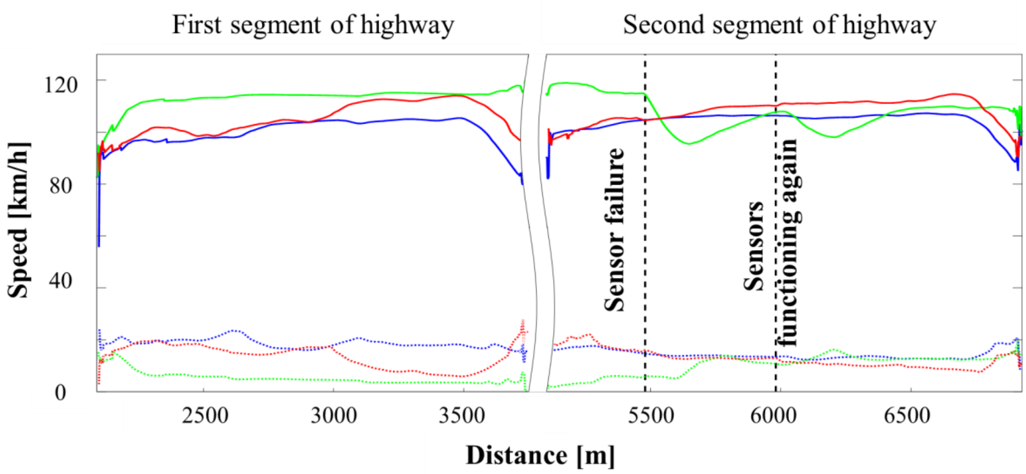


Figure I.A: Mean (solid line) and standard deviation (dashed line) of speed distributions calculated as a function of the distance travelled since the beginning of the simulation for the Baseline Condition (blue), the Experimental Condition 1 (green) and the Experimental Condition 2 (red).

Chapter 3 Driver behaviour characteristics during control transitions from full-range ACC to manual driving: an on-road experiment

FOTs have showed that the mean driver behaviour characteristics (values aggregated over 10-s intervals) change significantly after drivers deactivate ACC systems that are inactive at low speeds. However, these studies disregarded any temporal evolution of the driver behaviour characteristics over the 10-s intervals and did not control for the confounding effect of any additional control transitions initiated within these time intervals. Variations in the mean driver behaviour characteristics in medium-dense traffic flow conditions, which are more relevant to traffic operations, were not analysed explicitly. Therefore, the impact of these control transitions between ACC and manual driving on the driver behaviour characteristics was still unclear.

This thesis analysed the influence of control transitions from full-range ACC to manual driving on speed, acceleration, distance headway, and relative speed in an on-road experiment. Twenty-three participants drove a research vehicle equipped with full-range ACC on a 35.5 km freeway in Munich during peak hours. This data collection method allows controlling for potentially confounding factors such as road design and traffic conditions, which are common limitations of FOTs and naturalistic studies. Linear mixed-effects models were estimated to identify statistically significant changes in the driver behaviour characteristics over time a few seconds after manual control was resumed (*transition period*).

The results revealed that the time period after deactivation, the traffic density and the system state (*Inactive, Active,* and *Active and accelerate*) had a significant impact on the driver behaviour characteristics. At high densities, the speed decreased significantly after the ACC system was deactivated and it increased significantly after the system was overruled by pressing the gas pedal (Figure I.B). These speed reductions (or increments) can be interpreted as a compensation strategy to decrease (or increase) the feeling of risk and task difficulty.

Chapter 4 Factors influencing decisions to resume manual control in full-range ACC

FOTs have found that drivers may prefer to deactivate ACC in dense traffic flow conditions and before changing lanes. Despite the potential effects of these control transitions on traffic flow efficiency and safety, most of the models currently used to evaluate the impact of ACC do not describe control transitions. A few mathematical models have proposed deterministic decision rules for transferring control, ignoring heterogeneity between and within drivers in the decision-making process.

This thesis analysed the main factors that influence drivers’ decision to deactivate the ACC or overrule the system by pressing the gas pedal in a mixed logit model. The model was estimated based on the dataset collected in the on-road experiment.

The results revealed that drivers were more likely to deactivate the ACC and resume manual control when approaching a slower leader, when expecting vehicles cutting in, when driving above the ACC target speed, and before exiting the freeway. Drivers were more likely to overrule the ACC system by pressing the gas pedal a few seconds after the system has been activated, and when the vehicle decelerated. Everything else being equal, some drivers had higher probabilities to resume manual control. These findings suggest that a novel conceptual framework linking ACC system settings, driver behaviour characteristics, driver characteristics and environmental factors is needed to model driver behaviour during control transitions between ACC and manual driving.

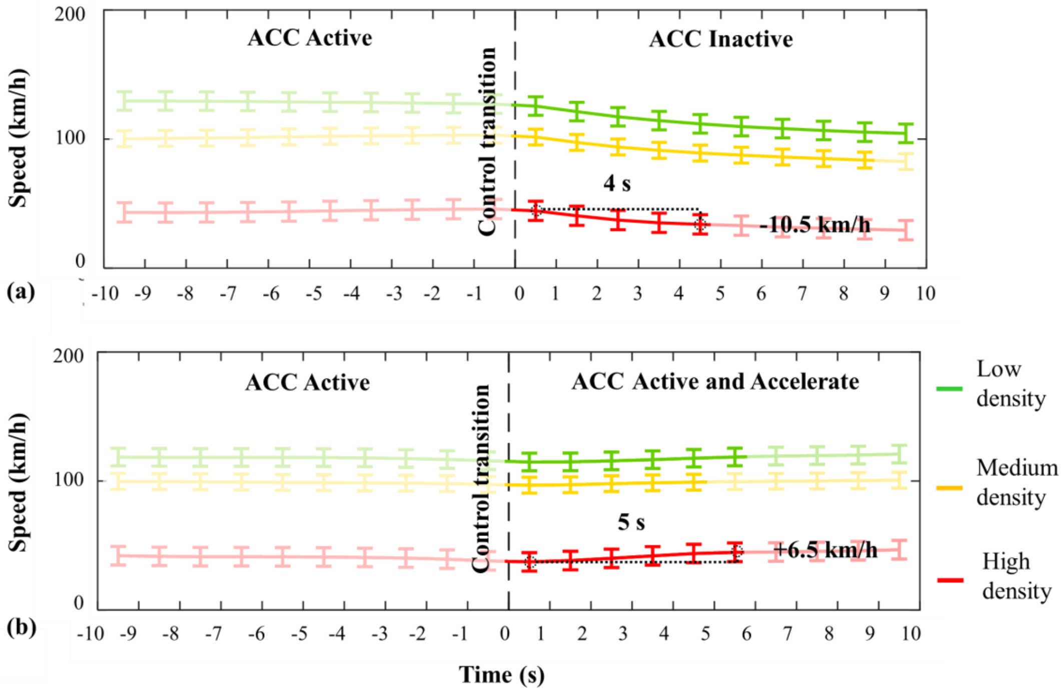


Figure I.B: Transitions from Active to Inactive (A to I, a) and from Active to Active and accelerate (A to AAc, b): estimated marginal means (solid line) and 95% confidence intervals of the mean estimates (error bars) of speed calculated as a function of system state and time in the interval 10 s before (-10, 0) and 10 s after (0, 10) the instant when the transition is initiated (dashed black line).

Chapter 5 Modelling decisions of control transitions and target speed regulations in full-range ACC based on Risk Allostasis Theory

Few studies have estimated the probability that drivers resume manual control in ACC based on empirical data. Drivers can adapt the ACC target speed to regulate the longitudinal control task and this possibility can influence their decision to resume manual control. However, a theoretical framework explaining driver decisions to transfer control and to regulate the target speed in full-range ACC was missing.

This thesis developed a modelling framework describing the underlying decision-making process of drivers with full-range ACC at an operational level, grounded on the Risk Allostasis Theory (RAT) (Figure I.C). Based on this theory, a driver will choose to resume manual control or to regulate the ACC target speed if its perceived level of risk feeling and task difficulty falls outside the range considered acceptable to maintain the system active. The feeling of risk and task difficulty evaluation was formulated as a generalized ordered probit model with random thresholds, which varied between drivers and within drivers over time. The ACC system state choices were formulated as logit models and the ACC target speed regulations as regression models, in which correlations between system state choices and target speed regulations were captured explicitly. This continuous-discrete choice model framework was able to address interdependencies across drivers' decisions in terms of causality, unobserved driver characteristics, and state dependency, and to capture inconsistencies in drivers' decision making that might be caused by human factors.

The model was estimated using maximum likelihood methods and the dataset collected in the on-road experiment with full-range ACC. Transitions to *Inactive* (deactivations) and ACC target speed reductions occurred most often in high risk feeling and task difficulty situations (high speeds, short distance headways, slower leader, and cut-ins expected), while transitions to *Active and accelerate* (overruling actions by pressing the gas pedal) and target speed increments in low risk feeling and task difficulty situations (low speeds, large distance headways and faster leader). Everything else being equal, some drivers were more likely to overrule the system by pressing the gas pedal. Figure I.D shows the impact of changes in the explanatory variables on the unconditional ACC system state choice probabilities and on the magnitude of the ACC target speed regulations.

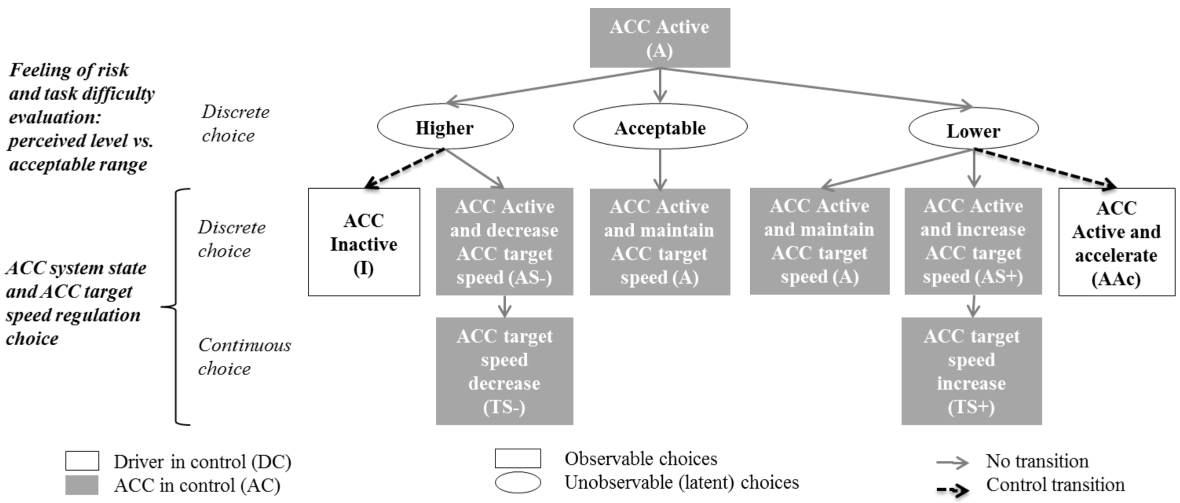


Figure I.C: Conceptual model for driver decisions to resume manual control and regulate the target speed in full-range ACC.

Chapter 6 Conclusions and recommendations

Findings in the driving simulator and in the on-road experiment showed that control transitions from full-range ACC to manual driving influence significantly the driver behaviour characteristics for a few seconds after manual control is resumed. To the best of the author's knowledge, this is the first study capturing explicitly the duration of the transition period and the magnitude of the corresponding variation in driver behaviour characteristics after drivers deactivated or overruled the ACC. From a behavioural point of view, the speed reductions (or increments) after manual control is resumed can be interpreted as a compensation strategy to decrease (or increase) the feeling of risk and task difficulty perceived, and the time interval associated as the duration needed to stabilize driving behaviour after manual control is resumed (transition period).

The findings point towards the relevance of developing car-following models that mimic driver response with ACC and that can be implemented into a microscopic traffic flow simulation. A car-following model grounded on feeling of risk and task difficulty can be developed to capture explicitly adaptations in driver behaviour characteristics during control transitions. In this model, the vehicle acceleration can be specified as a function of two additive terms, the first one representing regular car-following behaviour and the second one representing adaptation effects. Implementing this advanced car-following model into a microscopic traffic flow simulation, the impact of transitions from ACC to manual control on capacity, capacity drop and string stability can be investigated more realistically than in current microscopic simulations.

Drivers' decisions to resume manual control and to regulate the target speed in full-range ACC can be interpreted based on the RAT. This is one of the first attempts to develop a model framework explaining driver interaction with ADAS at an operational level based on theories developed in the field of driver psychology. The interpretation proposed is supported by the empirical findings in the choice models and by the analysis of the mean driver behaviour characteristics after manual control is resumed. The RAT contributes to shed light on the decision-making process of drivers. These findings point towards the importance of incorporating realistic driver behaviour mechanisms in driver behaviour models.

The choice model predicting control transitions and target speed regulations in full-range ACC is implementable into microscopic traffic flow models. To the best of author's knowledge, this is the first model predicting both transitions to manual control and target speed regulations in full-range ACC based on empirical data. Since the model framework is generic, it can be applied to predict driver's decision making at an operational level with other ADAS. The model can be implemented into a microscopic simulation to assess the impacts of ACC on traffic flow efficiency and safety accounting for control transitions and target speed regulations. The model can also be implemented into an ADAS to identify the situations in which drivers are likely to resume manual control.

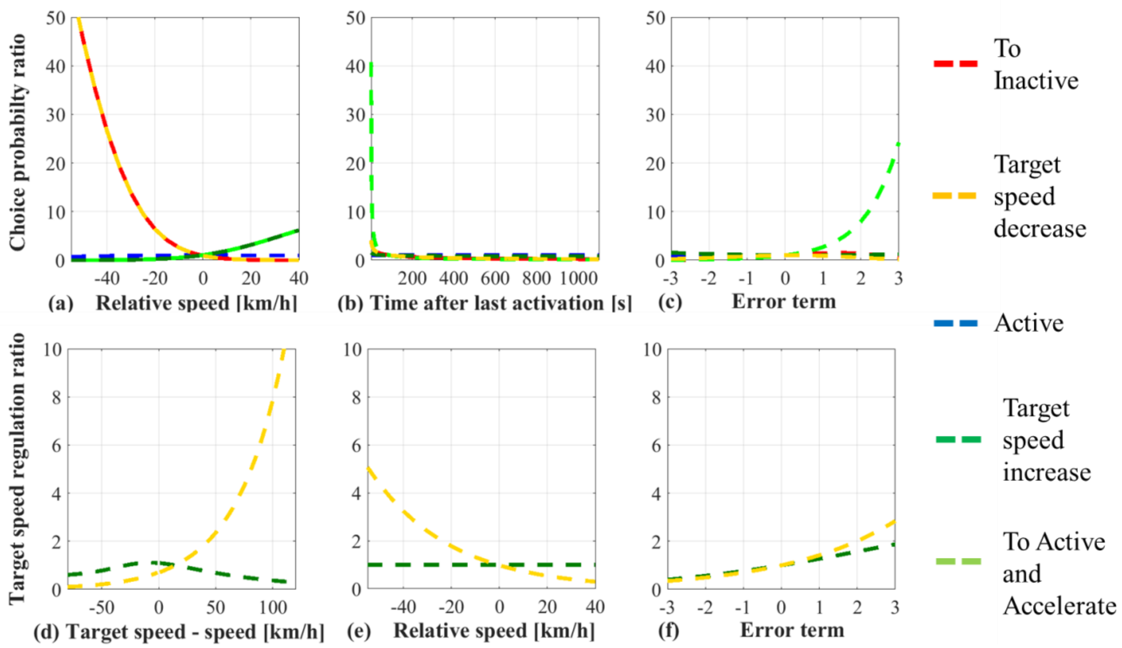


Figure I.D: Effect of (a) relative speed, (b) time after last activation, and (c) driver specific error term on the choice probability ratio (probability predicted divided by probability baseline observation) of the ACC system states. Effect of (d) target speed – speed, (e) relative speed, and (f) driver specific error term on the target speed regulation ratio (ACC target speed regulation predicted divided by ACC target speed regulation baseline observation) of regulating the ACC target speed.

Samenvattig

1 Inleiding

Geautomatiseerde voertuigen en geavanceerde rijassistentiesystemen zullen naar verwachting congestie, ongevallen en emissieniveaus verminderen. Geautomatiseerde voertuigen, met name voertuigen die coöperatief gedrag vertonen, kunnen de capaciteit van de weg vergroten, de stabiliteit van de verkeersstroom verbeteren en de uitstroom uit een file versnellen. Geautomatiseerde voertuigen zullen naar verwachting verkeersongevallen verminderen door het verminderen van de bestuurdersfouten, welke de oorzaak zijn van een groot aantal botsingen. De eerste stap naar het begrijpen van de impact van geautomatiseerde voertuigen op het wegverkeer is het onderzoeken van momenteel beschikbare systemen zoals Adaptive Cruise Control (ACC). ACC helpt bestuurders bij het handhaven van een beoogde snelheid en afstand tot de voorligger, en heeft daarom een direct effect op de longitudinale controletaak.

Field Operational Tests (FOTs) hebben aangetoond dat bestuurders de voorkeur kunnen geven aan het deactiveren van ACC systemen die niet actief zijn bij lage snelheden in drukke verkeersstroomomstandigheden, en voor het wisselen van rijstrook. Bovendien kunnen bestuurders worden gedwongen om het systeem te deactiveren vanwege de operationele beperkingen of een sensorstoring. Deze overgangen tussen automatisch en handmatig rijden worden *‘control transitions’* genoemd en kunnen een impact hebben op de efficiëntie en veiligheid van de verkeersstroom. De omstandigheden waarin deze overgangen plaatsvinden, hebben betrekking op de kenmerken van het rijtaakondersteunend systeem, de bestuurders zelf, de weg en de verkeersstroom.

Ondanks de potentiële effecten op verkeersoperaties, beschrijven de meeste volg- en rijbaanwisselmodellen die momenteel worden gebruikt om de impact van ACC te evalueren, geen ‘control transitions’. Enkele wiskundige modellen hebben deterministische beslisregels voorgesteld voor het overdragen van de besturing, en negeren mogelijke veranderingen in rijgedrag in de momenten voordat het systeem wordt geactiveerd en nadat het weer is gedeactiveerd. Tot op heden zijn beperkte inspanningen geleverd om ‘control transitions’ tussen Full-range-ACC en handmatig sturen te bestuderen, en te modelleren op een manier die geschikt zou zijn voor implementatie in microscopische modellen voor verkeersimulatie. De belangrijkste uitdagingen in deze richting omvatten (a) het ontwerpen van een rijsimulatorexperimenten en experimenten op de weg om het gedrag van de bestuurder tijdens ‘control transitions’ beter te kunnen begrijpen, (b) het analyseren van aanpassingen in het gedrag van de bestuurder wanneer de handmatige besturing wordt hervat, en (c) een framwork te ontwikkelen gebaseerd op de psychologische literatuur ten einde de keuzes van bestuurders te voorspellen om controle over te dragen.

De belangrijkste doelstellingen van dit proefschrift waren om empirisch inzicht te krijgen in het rijgedrag tijdens deze ‘control transitions’ en om te modelleren wanneer bestuurders de besluiten weer handmatige controle over te nemen. In dit proefschrift worden vier hoofdonderzoeksvragen als volgt behandeld: (1) Hoe gedraagt de bestuurder zich wanneer

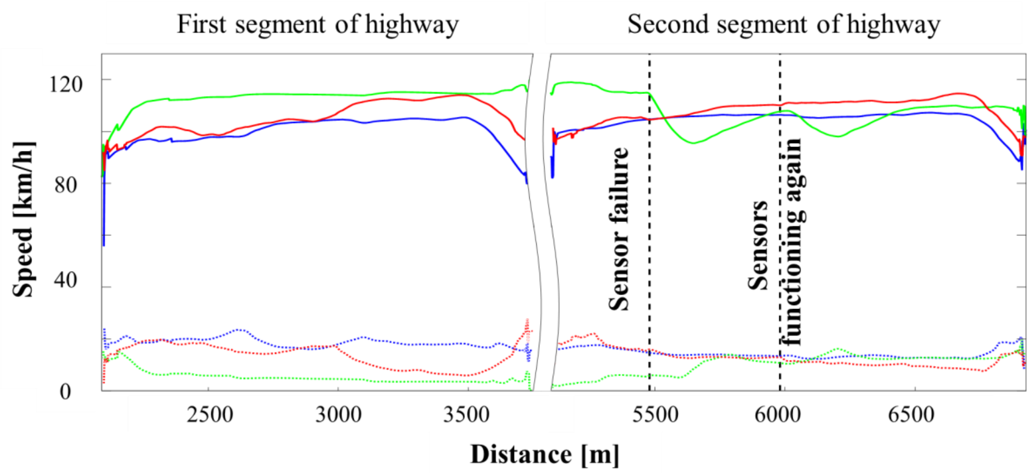
ACC met een volledig bereik deactiveert vanwege een sensorstoring? (2) Hoe veranderen de gedragkenmerken van de bestuurder in de loop van de tijd nadat de bestuurder de ACC volledig heeft gedeactiveerd of deze heeft overschreven door op het gaspedaal te drukken? (3) Welke factoren (rijgedrag, bestuurder en wegkenmerken) beïnvloeden de beslissingen van bestuurders om de handmatige besturing in Full-range-ACC te hervatten? (4) Hoe modelleren we de beslissingen van de bestuurder om de handmatige besturing te hervatten of de doelsnelheid in Full-range-ACC te reguleren?

2 Karakteristieken van het stuurgedrag tijdens 'control transitions' van Full-range-ACC naar handmatig rijden: een rijsimulator-experiment

Het rijgedrag van de bestuurder tijdens 'control transitions' tussen ACC en handmatig rijden is geanalyseerd in zowel rijsimulator- als FOT-onderzoeken. De meeste simulatorstudies zijn uitgevoerd in het human factors onderzoeksgebied, en hebben zich voornamelijk gericht op reactietijden in situaties waar de automatisering faalt. FOTs zijn voornamelijk uitgevoerd binnen de verkeerskunde met ACC-systemen die inactief zijn bij lage snelheden. Er ontbrak echter een gecontroleerd experiment met onderzoek naar de invloed van 'control transitions' op de longitudinale gedragskenmerken van de bestuurder.

Dit proefschrift analyseerde de invloed van 'control transitions' bij full-range-ACC en handmatig rijden op snelheid, versnelling en afstand tot voorligger, op basis van gegevens verzameld in een driversimulator-experiment. Zevenenzestig deelnemers werden willekeurig aan een van de drie experimentele condities toegewezen en voltooiden het experiment met succes. In de basisconditie reden de deelnemers handmatig. In de eerste experimentele situatie werd een sensorstoring gesimuleerd op een specifieke locatie, waarbij het voertuig vertraagde en van de bestuurder werd verwacht dat ze de controle van het voertuig overnamen. In de tweede experimentele situatie activeerde en deactiveerde de bestuurders de ACC naar eigen inzicht door middel van een knop.

Statistische tests wezen uit dat de verdeling van snelheid, versnelling en afstand tot de voorligger significant verschilde tussen de drie condities. In de eerste experimentele toestand daalde de snelheid na de sensorstoring (Figuur I.A). Deze resultaten lijken in overeenstemming te zijn met eerdere bevindingen en suggereren dat 'control transitions' tussen ACC en handmatig rijden de kenmerken van het longitudinale bestuurdersgedrag aanzienlijk kunnen beïnvloeden.



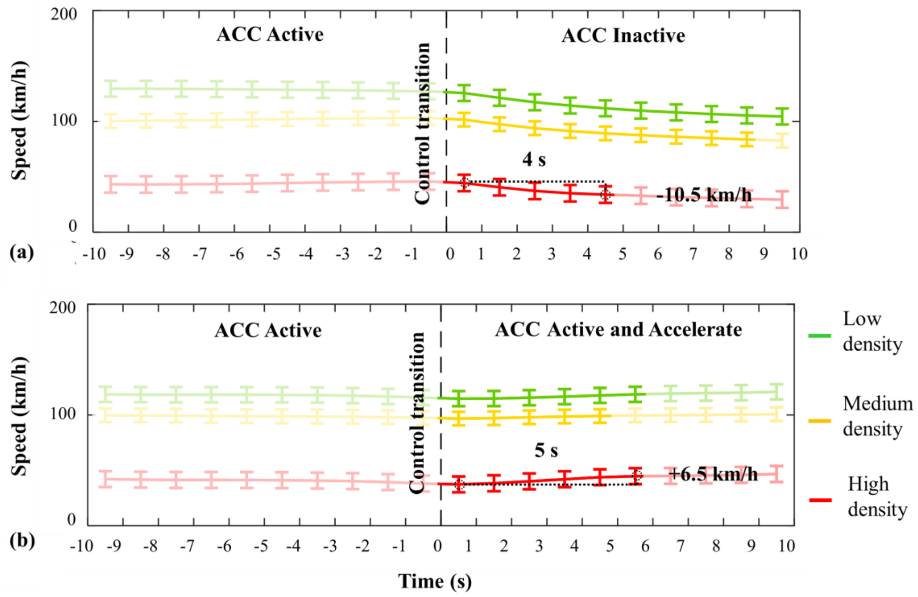
Figuur I.A: Gemiddelde (getrokken lijn) en standaardafwijking (stippellijn) van snelheidsverdelingen berekend als een functie van de afgelegde afstand sinds het begin van de simulatie voor de basislijnvoorwaarde (blauw), de experimentele toestand 1 (groen) en de experimentele voorwaarde 2 (rood).

3 Karakteristieken van het stuurgedrag tijdens 'control transitions' van full-range-ACC naar handmatig rijden: een experiment op de weg

FOTs hebben aangetoond dat het rijgedrag (waarden geaggregeerd over intervallen van 10 s) aanzienlijk verandert nadat bestuurders ACC-systemen deactiveren die bij lage snelheden inactief zijn. Deze studies negeerden echter de verandering van het rijgedrag binnen de intervallen van 10 seconden, en controleerden niet voor het verstorende effect van eventuele extra 'control transitions' die binnen deze tijdsintervallen werden geïnitieerd. Variaties in het rijgedrag in gemiddeld drukke verkeersomstandigheden, die representatiever zijn voor veelvoorkomende verkeersomstandigheden, werden niet expliciet geanalyseerd. Tot op heden is de impact van 'control transitions' tussen ACC en handmatig rijden op het rijgedrag in deze situaties nog steeds onduidelijk.

Dit proefschrift analyseerde de invloed van 'control transitions' van Full-range-ACC naar handmatig rijden op snelheid, versnelling, volgafstand en relatieve snelheid in een experiment op de weg. Drieëntwintig deelnemers reden tijdens de spits in een onderzoeksvoertuig uitgerust met full-range-ACC op een stuk snelweg in München van 35.5 km. Deze methode van gegevensverzameling maakte het mogelijk om voor mogelijk verstorende factoren, zoals wegontwerp en verkeersomstandigheden, te controleren. Dit voorkomt een van de beperkingen die FOTs en naturalistische onderzoeken vaak hebben. Lineaire 'mixed-effect' modellen werden gebruikt om statistisch significante veranderingen in gedrag van de bestuurder over een periode van enkele seconden nadat de handmatige besturing was hervat vast te stellen (*overgangsperiode*).

Uit de resultaten bleek dat de tijdsperiode na de-activering, de verkeersdichtheid en de systeemstatus (*Inactief*, *Actief* en *Actief en versnellen*) allen een significant effect hadden op het rijgedrag. Bij hoge dichtheden nam de snelheid aanzienlijk af nadat het ACC-systeem was gedeactiveerd, en nam de snelheid aanzienlijk toe nadat het systeem werd overschreven doordat de bestuurder op het gaspedaal drukte (Figuur I.B). Deze snelheidsveranderingen kunnen worden geïnterpreteerd als een compensatiestrategie om de beleving van risico- en taakcomplexiteit te verminderen (of te vergroten).



Figuur I.B: Overgangen van actief naar inactief (A naar I, a) en van actief naar actief en versnellen (A naar AAc, b): geschatte marginale gemiddelden (vaste lijn) en 95% betrouwbaarheidsintervallen van de gemiddelde schattingen (foutbalken) van snelheid berekend als een functie van systeemstatus en tijd in het interval 10 seconden vóór (-10, 0) en 10 seconden na (0,10) het moment waarop de overgang wordt gestart (gestreepte zwarte lijn).

4 Factoren die beslissingen om handmatige besturing in Full-range-ACC te hervatten beïnvloeden

Eerdere FOTs hebben aangetoond dat bestuurders ACC liever deactiveren in drukke verkeersstroomomstandigheden, en vlak voordat ze van rijstrook veranderen. Ondanks de potentiële effecten van deze 'control transitions' op de verkeersstroomefficiëntie en -veiligheid, beschrijven de meeste modellen die momenteel worden gebruikt om de impact van ACC te evalueren, geen 'control transitions'. Een handvol wiskundige modellen hebben deterministische beslisregels voorgesteld voor het overdragen van controle, waarbij heterogeniteit tussen en binnen bestuurders in het besluitvormingsproces wordt genegeerd.

Dit proefschrift analyseerde de belangrijkste factoren die van invloed zijn op het besluit van bestuurders om de ACC te deactiveren of het systeem te negeren door het gaspedaal in te drukken met een mixed logit model. Modelparameters zijn geschat op basis van de dataset die is verzameld in het hiervoor beschreven experiment op de weg.

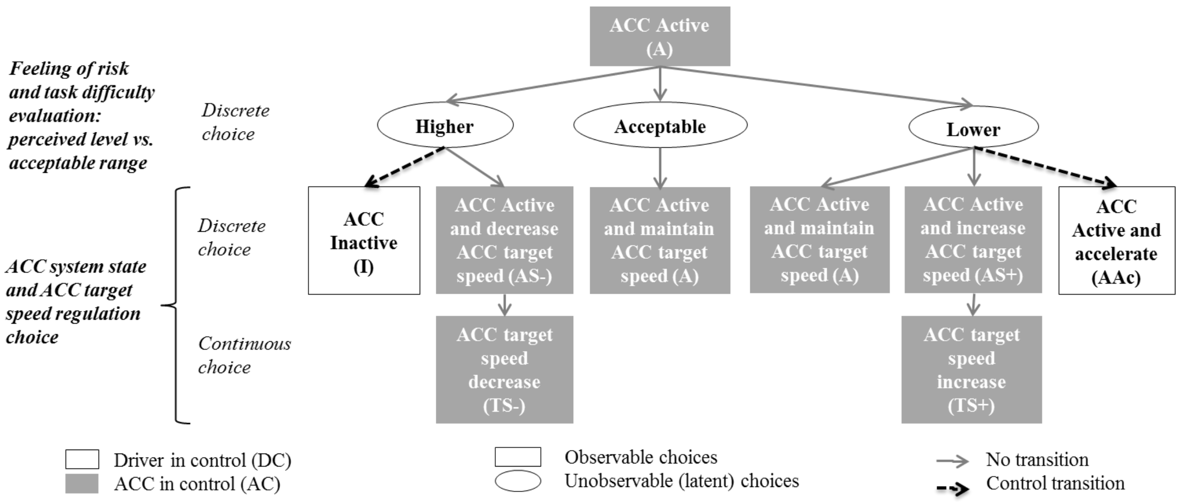
De resultaten toonden aan dat bestuurders de ACC eerder zouden deactiveren en handmatige besturing hervatten, bij het naderen van een langzamere voorligger, bij het verwachten van invoegende voertuigen, bij het rijden boven de ACC-doelsnelheid en voor het verlaten van de snelweg. Het was waarschijnlijker dat bestuurders in de eerste seconden na activatie van het ACC-systeem het gaspedaal nog indrukten en zo het systeem negeerden, indien het voertuig vertraagde. Sommige bestuurders vertoonden een grotere waarschijnlijkheid om de handmatige besturing te hervatten dan anderen. Deze bevindingen suggereren dat een nieuw conceptueel kader nodig is, welke ACC-systeeminstellingen, gedragskenmerken van de bestuurder, persoonlijkheidskenmerken van de bestuurder, en omgevingsfactoren koppelt. Een dergelijk kader kan helpen bij het modelleren van het gedrag van de bestuurder tijdens ‘control transitions’ tussen ACC en handmatig rijden.

5 Modellering van beslissingen van ‘control transitions’ en streefsnelheidsregels in Full-range-ACC op basis van de ‘Risk Allostasis Theory’

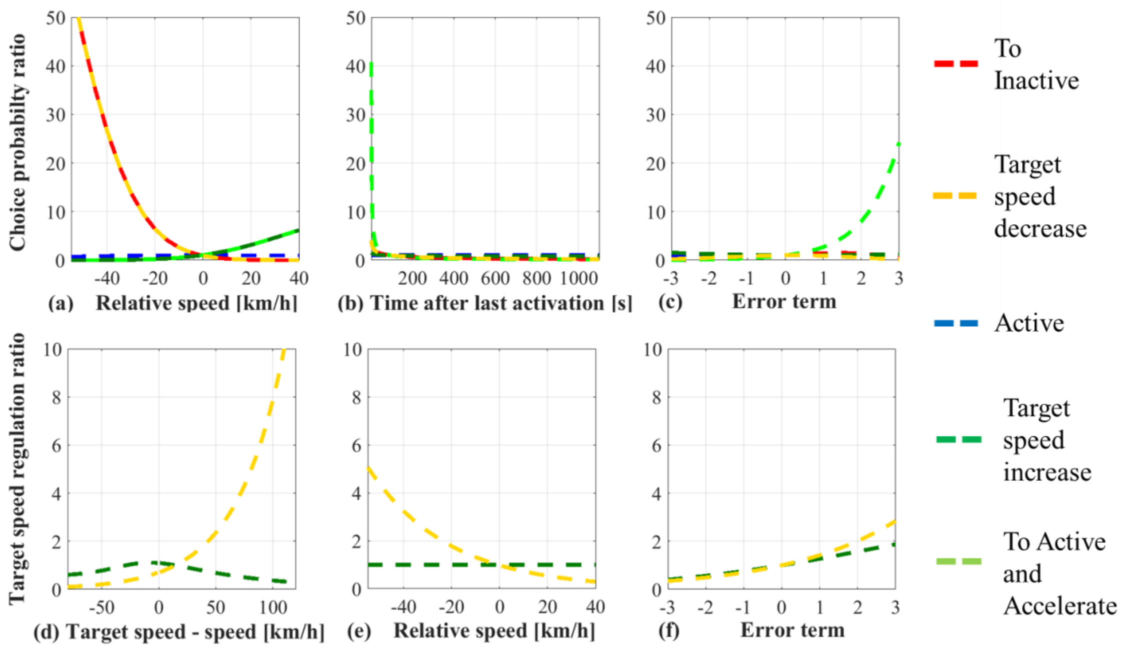
Weinig studies hebben empirische gegevens gebruikt om de waarschijnlijkheid te evalueren dat bestuurders de handmatige besturing in ACC hervatten. Bestuurders kunnen de ACC-doelsnelheid aanpassen om de longitudinale controletaak te regelen, en deze mogelijkheid kan hun beslissing om de handmatige besturing te hervatten, beïnvloeden. Er ontbrak echter een theoretisch raamwerk waarin de beslissingen van de bestuurder werden uitgelegd om de besturing over te dragen en de doelsnelheid in Full-range-ACC te regelen.

Dit proefschrift heeft een theoretisch raamwerk ontwikkeld dat het onderliggende besluitvormingsproces beschrijft van bestuurders met full-range-ACC op operationeel niveau, gebaseerd op de Risk Allostasis Theory (RAT) (Figuur I.C). Op basis van deze theorie zal een bestuurder kiezen om de handmatige besturing te hervatten of om de ACC-doelsnelheid te regelen, als het waargenomen niveau van risicogevoel en taakcomplexiteit buiten het bereik valt dat als aanvaardbaar wordt beschouwd om het systeem actief te houden. Het gevoel van risico- en taakcomplexiteitsevaluatie werd geformuleerd als een ‘generalised ordered probit model’ met willekeurige drempelwaardes, die in de tijd varieerden tussen bestuurders en binnen bestuurders. De keuzes van het ACC-systeem zijn geformuleerd als logit-modellen en de ACC-snelheidsregelgeving als regressiemodellen, waarin correlaties tussen systeemstaatkeuzes en streefsnelheidsregels expliciet werden vastgelegd. Dit ‘continuous-discrete’ keuzemodel framework was in staat om te gaan met de onderlinge afhankelijkheden tussen de beslissingen van de bestuurder in termen van causaliteit, niet-geobserveerde kenmerken van de bestuurder en afhankelijkheid van de staat, en om inconsistenties vast te stellen in de besluitvorming van bestuurders die veroorzaakt zou kunnen worden door menselijke factoren.

Modelparameters zijn geschat met behulp van ‘maximum likelihood’ methoden, en de dataset die is verzameld in het experiment op de weg met full-range-ACC. Overgangen naar inactieve (deactiveringen) en ACC-doelsnelheidsreducties deden zich het meest voor in situaties met veel risico's en hoge taakcomplexiteit (hoge snelheden, korte afstanden, langzamere leider en verwachte cut-ins), terwijl overgangen naar actief en versnellen (systeem overschrijven door het gaspedaal in te drukken) en richt snelheidstoenames in situaties met een laag risico en taakproblemen (lage snelheden, grote afstanden en snellere leider). Sommige bestuurders vertoonden een verhoogde kans om het systeem te overschrijven door op het gaspedaal te drukken. Figuur I.D toont de impact van wijzigingen in de verklarende variabelen op de kansverhouding voor de gemaakte keuzes voor de ACC-systeemstatussen en op de regulatieverhouding van het ACC doelsnelheid.



Figuur I.C: Conceptueel model voor beslissingen van de bestuurder om de handmatige besturing te hervatten en de doelsnelheid te regelen in Full-range-ACC.



Figuur I.D: Effect van (a) relatieve snelheid, (b) tijd sinds laatste activering, en (c) driver-specifieke foutterm op de kansverhouding voor de gemaakte keuzes (voorspelde waarschijnlijkheid gedeeld door waarschijnlijkheids-baselineobservatie) voor de ACC-systeemstatussen. Effect van (d) doelsnelheid - snelheid, (e) relatieve snelheden, en (f) driver-specifieke foutterm op de regulatieverhouding van de doelsnelheid (ACC-voorspelde snelheidsregeling voorspeld gedeeld door ACC-doelsnelheidsregulatie basislijnwaarneming) van het reguleren van het ACC doelsnelheid.

6 Conclusies

Bevindingen in de rijsimulator en in het experiment op de weg toonden aan dat 'control transitions' van Full-range-ACC naar handmatig rijden het gedrag van de bestuurder aanzienlijk beïnvloeden gedurende een paar seconden nadat de handmatige besturing is hervat. Naar beste weten van de auteur is dit de eerste studie waarin expliciet de duur van de overgangsperiode en de omvang van de overeenkomstige variatie in gedragskenmerken van de bestuurder worden vastgelegd nadat de bestuurders de ACC hebben gedeactiveerd of overschreven. Vanuit gedragsoogpunt kunnen de snelheidsverminderingen (of toenamen) na handmatig hervatten worden geïnterpreteerd als een compensatiestrategie om het gevoel van risico- en taakcomplexiteit dat wordt waargenomen te verminderen (of te vergroten) en het tijdsinterval dat is gekoppeld aan de benodigde duur om het rijgedrag te stabiliseren nadat de handmatige besturing is hervat (overgangsperiode).

De bevindingen wijzen op de relevantie van het ontwikkelen van auto-volg-modellen die de reactie van de bestuurder nabootsen met ACC en die kunnen worden geïmplementeerd in een microscopische verkeersstroomsimulatie. Een auto-volg-model gebaseerd op een gevoel van risico en taakcomplexiteit kan worden ontwikkeld om expliciet aanpassingen in gedrag van de bestuurder tijdens 'control transitions' te voorspellen. In dit model kan de voertuigacceleratie worden gespecificeerd als een functie van twee additieve termen, de eerste die het reguliere volggedrag weergeeft en de tweede die aanpassingseffecten vertegenwoordigt. Door dit geavanceerde volgmodel in een microscopische verkeersstroomsimulatie te implementeren, kan de impact van overgangen van ACC naar handmatige controle op capaciteit, capaciteitsverlies en stringstabiliteit realistischer worden onderzocht dan in huidige microscopische simulaties.

De beslissing van chauffeurs om de handmatige besturing te hervatten en de doelsnelheid in Full-range-ACC te regelen, kan worden geïnterpreteerd op basis van RAT. Dit is een van de eerste pogingen om een framework te ontwikkelen dat de interactie tussen de bestuurder en ADAS op operationeel niveau uitlegt, gebaseerd op theorieën die zijn ontwikkeld op het gebied van de verkeerspsychologie. De voorgestelde interpretatie wordt ondersteund door de empirische bevindingen in de keuzemodellen en door de analyse van de gemiddelde gedragskenmerken van de bestuurder nadat de handmatige besturing is hervat. Deze bevindingen wijzen op het belang van het opnemen van realistische gedragsmechanismen van de bestuurder in rijgedragsmodellen.

Het keuzemodel dat 'control transitions' en doelsnelheidsregels in Full-range-ACC voorspelt, kan worden geïmplementeerd in microscopische verkeersstroommodellen. Naar beste weten van de auteur is dit het eerste model dat zowel overgangen naar handmatige regeling als streefsnelheidsregels voorspelt in Full-range-ACC op basis van empirische gegevens. Aangezien het modelraamwerk generiek is, kan het worden toegepast om de besluitvorming van de bestuurder op operationeel niveau met andere ADAS te voorspellen. Het model kan worden geïmplementeerd in een microscopische simulatie om de effecten van ACC op de verkeersstroomefficiëntie en veiligheidsaccounting voor 'control transitions' en streefsnelheidsvoorschriften te beoordelen. Het model kan ook worden geïmplementeerd in een ADAS om de situaties te identificeren waarin bestuurders waarschijnlijk de handmatige besturing zullen hervatten.

Sintesi

Capitolo 1 Introduzione

Si prevede che i veicoli automatici e i sistemi avanzati di assistenza alla guida riducano la congestione, gli incidenti e i livelli di emissioni. I veicoli automatici, in particolare quelli che possono mostrare un comportamento cooperativo, possono aumentare la capacità della strada, migliorare la stabilità del flusso del traffico e accelerare l'uscita da una coda. Si prevede che i veicoli automatici attenuino gli incidenti stradali prevenendo e riducendo errori da parte dei guidatori, i quali sono responsabile della maggior parte degli incidenti. Il primo passo verso la comprensione dell'impatto dei veicoli automatici sul traffico stradale consiste nello studio dei sistemi attualmente disponibili come l'Adaptive Cruise Control (ACC). L'ACC aiuta i guidatori a mantenere una velocità di crociera e una distanza desiderata e quindi ha un effetto diretto sul compito di controllo longitudinale.

Esperimenti su strada di larga scala (*Field Operational Tests*) hanno dimostrato che i guidatori preferiscono disattivare sistemi ACC inattivi alle basse velocità in condizioni di flusso di traffico intense e prima di cambiare corsia. Inoltre, i guidatori possono essere costretti a disattivare il sistema a causa dei suoi limiti operativi o di un guasto del sensore. Queste transizioni tra la guida automatica e manuale sono chiamate *transizioni di controllo* e possono avere un impatto sull'efficienza e sulla sicurezza del flusso di traffico. Le circostanze in cui si verificano queste transizioni sono legate alle caratteristiche del sistema di assistenza alla guida, dei guidatori, della strada e del flusso di traffico.

Nonostante i potenziali effetti sul traffico, la maggior parte dei modelli microscopici attualmente utilizzati per valutare l'impatto dell'ACC sui flussi di traffico non descrivono le transizioni di controllo. Alcuni modelli matematici hanno proposto regole decisionali deterministiche per le transizioni di controllo e hanno ignorato possibili adattamenti nel comportamento di guida manuale prima che il sistema sia attivato e dopo che il sistema è stato disattivato. Ad oggi, sono stati compiuti sforzi limitati per studiare e modellare le transizioni di controllo tra ACC attivi anche a basse velocità (*full-range ACC*) e guida manuale in un modo adatto all'implementazione in modelli microscopici di simulazione del traffico. Le principali *sfide* in questa direzione includono (1) progettare esperimenti con un simulatore di guida e su strada per comprendere meglio il comportamento del guidatore durante le transizioni di controllo, (2) analizzare adattamenti nelle caratteristiche del comportamento del guidatore quando i guidatore riprendono il controllo manuale, e (3) sviluppare un modello basato su teorie di psicologia del guidatore per prevedere le scelte dei guidatore di trasferire il controllo.

Gli *obiettivi* principali di questa tesi erano (1) ottenere informazioni sperimentali sul comportamento di guida durante queste transizioni di controllo (Sfida 2) e (2) modellare le decisioni dei guidatori di riprendere il controllo manuale (Sfida 3). Per raggiungere questi obiettivi, sono stati raccolti dati in esperimenti con simulatore di guida e su strada (Sfida 1). Per ottenere informazioni sugli adattamenti delle caratteristiche del comportamento del guidatore durante le transizioni di controllo (Obiettivo 1), questa tesi ha affrontato due *domande di ricerca* principali come segue: (1) come si comportano i guidatori quando il full-range ACC si disattiva a causa di un guasto del sensore (Capitolo 2)? (2) come cambiano nel tempo le caratteristiche del comportamento del guidatore dopo che il guidatore ha disattivato il full-range ACC oppure lo ha sospeso temporaneamente premendo l'acceleratore (Capitolo 3)? Per sviluppare un modello che prevede le scelte dei guidatori di trasferire controllo e regolare la velocità di crociera dell'ACC (Obiettivo 2), sono state affrontate le seguenti *domande di ricerca*: (3) quali fattori (caratteristiche del guidatore, del comportamento del guidatore, e della strada) influenzano le decisioni dei guidatori di riprendere il controllo manuale con il full-range ACC (Capitolo 4)? (4) come si possono modellare le decisioni dei guidatori di riprendere il controllo manuale e di regolare la velocità di crociera con il full-range ACC (Capitolo 5)?

Capitolo 2 Caratteristiche del comportamento del guidatore durante le transizioni di controllo tra full-range ACC e guida manuale: un esperimento con il simulatore di guida

Il comportamento del guidatore durante le transizioni di controllo tra l'ACC e la guida manuale è stato analizzato in esperimenti con il simulatore di guida e su strada. La maggior parte degli studi con i simulatori di guida sono stati condotti nel campo dei fattori umani e si sono concentrati sui tempi di reazione in caso di guasto dell'automazione. Esperimenti su strada sono stati condotti nel campo dell'ingegneria del traffico con sistemi ACC inattivi alle basse velocità. Tuttavia, mancava un esperimento finalizzato a studiare l'impatto delle transizioni di controllo sulle caratteristiche del comportamento longitudinale del guidatore con un alto grado di controllabilità.

Questa tesi ha analizzato l'effetto delle transizioni di controllo tra il full-range ACC e la guida manuale su velocità, accelerazione e intervallo temporale fra veicoli (*time headway*) in base ai dati raccolti in un esperimento con il simulatore di guida. Sessantasette partecipanti sono stati assegnati a una delle tre condizioni in modo casuale e hanno completato con successo l'esperimento. Nella condizione di riferimento, i partecipanti hanno guidato manualmente. Nella prima condizione sperimentale, un guasto del sensore è stato simulato in una posizione specifica, dove il veicolo ha rallentato e si prevedeva che i guidatori riprendessero il controllo manuale. Nella seconda condizione sperimentale, i guidatori attivavano e disattivavano l'ACC premendo un pulsante ogni volta che lo desideravano.

I test statistici hanno indicato che le distribuzioni di velocità, accelerazione e time headway sono significativamente diverse nelle tre condizioni. Nella prima condizione sperimentale, la velocità è diminuita dopo il guasto del sensore (Figura I.A). Questi risultati sembrano essere coerenti con i risultati precedenti e suggeriscono che le transizioni di controllo tra ACC e la guida manuale possono influenzare in modo significativo le caratteristiche del comportamento longitudinale del guidatore.

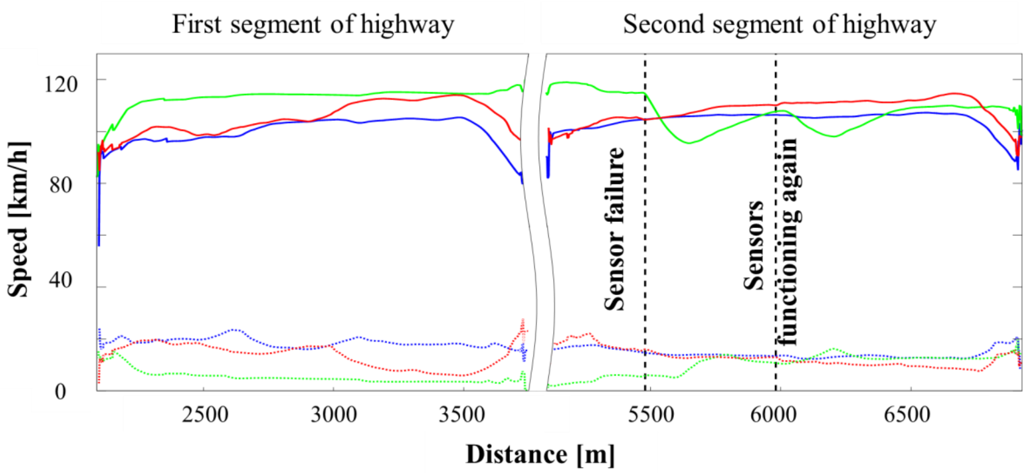


Figura I.A: Media (linea continua) e deviazione standard (linea tratteggiata) delle distribuzioni di velocità calcolate in funzione della distanza percorsa dall'inizio della simulazione per la condizione di riferimento (blu), la prima condizione sperimentale (verde) e la seconda condizione sperimentale (rosso).

Chapter 3 Caratteristiche del comportamento del guidatore durante le transizioni di controllo tra full-range ACC e guida manuale: un esperimento su strada

Esperimenti su strada hanno dimostrato che le caratteristiche medie del comportamento del guidatore (valori aggregati in base ad intervalli di 10 s) cambiano significativamente dopo che i guidatori disattivano sistemi ACC inattivi alle basse velocità. Tuttavia, questi studi non hanno tenuto conto dell'evoluzione temporale delle caratteristiche del comportamento del guidatore durante gli intervalli di 10 s e non hanno analizzato l'effetto di altre transizioni di controllo eventualmente eseguite durante questi intervalli di tempo. Variazioni nelle caratteristiche medie del comportamento del guidatore in condizioni di flusso di traffico medio-intenso, le quali sono più importanti per valutare l'efficienza del traffico, non sono state analizzate esplicitamente. Pertanto, non era ancora chiaro l'impatto di queste transizioni di controllo tra l'ACC e la guida manuale sulle caratteristiche del comportamento del guidatore.

Questa tesi ha analizzato l'effetto delle transizioni di controllo dal full-range ACC alla guida manuale su velocità, accelerazione, distanza fra veicoli (*distance headway*) e velocità relativa fra veicoli in un esperimento su strada. Ventitré partecipanti hanno guidato un veicolo di ricerca equipaggiato con full-range ACC su un tratto di autostrada lungo 35,5 km a Monaco durante le ore di punta. Questo metodo di raccolta dei dati consente di controllare l'effetto di fattori come la progettazione stradale e le condizioni del traffico, che sono limiti comuni degli esperimenti su strada di larga scala e degli studi naturalistici. Modelli lineari a effetti misti (*linear mixed-effects models*) sono stati stimati per identificare adattamenti statisticamente significativi nelle caratteristiche del comportamento del guidatore nel tempo, pochi secondi dopo il ripristino del controllo manuale (*periodo di transizione*).

I risultati hanno rivelato che il periodo di tempo dopo la disattivazione, la densità del traffico e lo stato del sistema (inattivo, attivo, attivo e accelerato) hanno avuto un impatto significativo sulle caratteristiche del comportamento del guidatore. In condizioni di traffico intenso, la velocità è diminuita significativamente dopo che il sistema ACC è stato disattivato ed è aumentata significativamente dopo che il sistema è stato sospeso temporaneamente premendo il pedale dell'acceleratore (Figura I.B). Queste riduzioni (o incrementi) di velocità possono essere interpretate come una strategia di compensazione per diminuire (o aumentare) la sensazione di rischio e la difficoltà del compito.

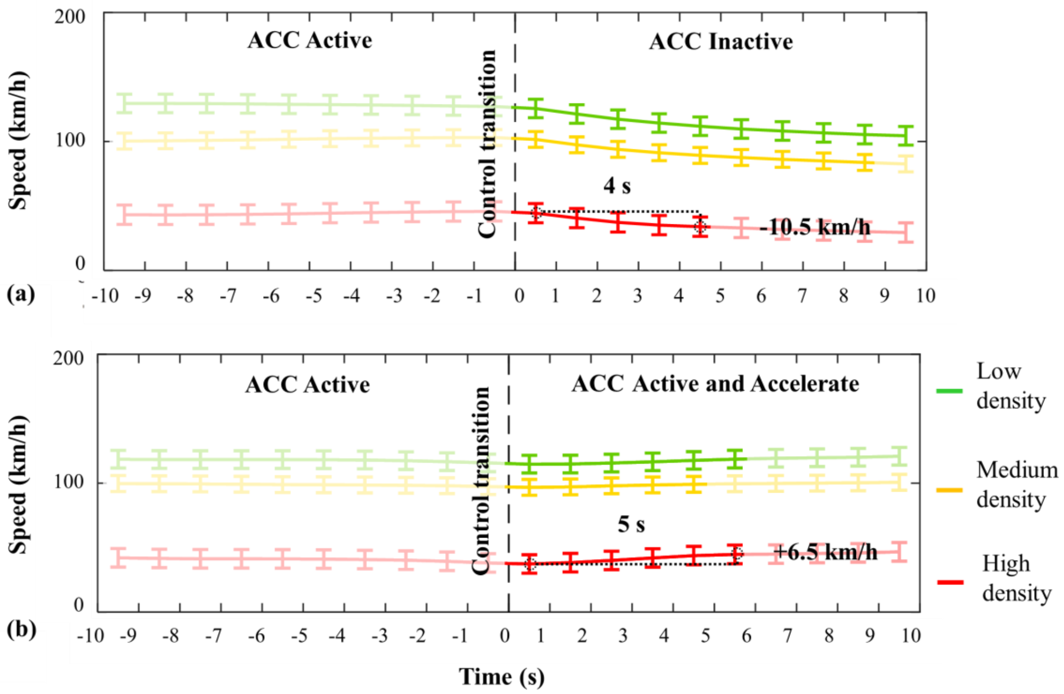


Figura I.B: Transizioni da attivo a inattivo (da A ad I, a) e da attivo ad attivo e accelerato (da A ad AAc, b): medie marginali stimate (linea continua) e intervalli di confidenza per le medie stimate pari al 95% (barre di errore) di velocità calcolata in funzione dello stato del sistema e del tempo nell'intervallo 10 s prima (-10, 0) e 10 s dopo (0, 10) l'istante in cui viene eseguita la transizione (linea tratteggiata nera).

Capitolo 4 Fattori che influenzano le decisioni di riprendere il controllo manuale con il full-range ACC

Esperimenti su strada hanno dimostrato che i guidatori preferiscono disattivare l'ACC in condizioni di flusso di traffico intenso e prima di cambiare corsia. Nonostante i potenziali effetti di queste transizioni di controllo sull'efficienza e sulla sicurezza del flusso di traffico, la maggior parte dei modelli attualmente utilizzati per valutare l'impatto dell'ACC non descrivono le transizioni di controllo. Alcuni modelli matematici hanno proposto regole decisionali deterministiche per il trasferimento del controllo, ignorando variabilità fra (*between*) ed entro (*within*) i guidatori nel processo decisionale.

Questa tesi ha analizzato i principali fattori che influenzano le decisioni dei guidatori di disattivare l'ACC o di sospendere temporaneamente il sistema premendo il pedale dell’acceleratore usando un modello mixed logit. Il modello è stato stimato in base ai dati raccolti nell'esperimento su strada.

I risultati hanno rivelato che i guidatori avevano maggiori probabilità di disattivare l'ACC e riprendere il controllo manuale quando si avvicinavano ad un veicolo (leader) più lento, quando prevedevano veicoli in entrata, quando guidavano al di sopra della velocità di crociera dell'ACC e prima di uscire dall'autostrada. I guidatori avevano più probabilità di annullare il sistema ACC premendo l'acceleratore pochi secondi dopo che il sistema era stato attivato e quando il veicolo rallentava. A parità di condizioni, alcuni guidatori avevano maggiori probabilità di riprendere il controllo manuale. Questi risultati suggeriscono che, per modellare il comportamento del guidatore durante le transizioni di controllo tra l'ACC e la guida manuale, è necessaria una nuova struttura teorica che colleghi le impostazioni del sistema ACC, le caratteristiche del comportamento del guidatore, le caratteristiche del guidatore e i fattori ambientali.

Capitolo 5 Modellizzazione delle decisioni di transizioni di controllo e di regolazione della velocità di crociera con il full-range ACC basata sulla teoria di allostasi del rischio

Pochi studi hanno stimato la probabilità che i guidatori riprendano il controllo manuale con l'ACC sulla base di dati sperimentali. I conducenti possono adattare la velocità di crociera dell'ACC per regolare il compito di controllo longitudinale e questa possibilità può influenzare la loro decisione di riprendere il controllo manuale. Tuttavia, mancava una struttura teorica che spiegasse le decisioni dei guidatori di trasferire il controllo e di regolare la velocità di crociera con il full-range ACC.

Questa tesi ha sviluppato un modello che descrive il processo decisionale dei guidatori con il full-range ACC a livello operativo, basato sulla teoria di allostasi del rischio (*risk allostasis theory*) (Figura I.C). Sulla base di questa teoria, un guidatore sceglierà di riprendere il controllo manuale o di regolare la velocità di crociera dell'ACC se il suo livello percepito della sensazione di rischio e della difficoltà del compito non rientrano nell'intervallo considerato accettabile per mantenere attivo il sistema. La valutazione della sensazione di rischio e della difficoltà del compito sono state formulate come un modello probit ordinale generalizzato con intervalli random (*generalized ordered probit model with random thresholds*), che variavano fra i guidatori ed entro i guidatori nel tempo. Le scelte dello stato del sistema ACC sono state formulate come modelli logit e la regolazione della velocità di crociera dell'ACC come modelli di regressione, in cui le correlazioni tra la scelta dello stato del sistema e le regolazione della velocità di crociera sono state catturate esplicitamente. Questo modello di scelta continua e discreta è stato in grado di rappresentare le interdipendenze tra le decisioni dei conducenti in termini di causalità, caratteristiche dei guidatori non osservate, e dipendenza dalla situazione e di catturare incoerenze nel processo decisionale dei guidatori che potrebbero essere causate da fattori umani.

Il modello è stato stimato utilizzando metodi di massima verosimiglianza e la base di dati raccolta nell'esperimento su strada con il full-range ACC. Le transizioni a sistema *inattivo* (disattivazioni) e le riduzioni della velocità di crociera dell'ACC si sono verificate molto spesso in situazioni di alto rischio e difficoltà (velocità elevate, brevi distance headways, veicolo di fronte più lento e veicoli in entrata previsti), mentre le transizioni a sistema *attivo e accelerato* (sospensione temporanea del sistema premendo il pedale dell'acceleratore) e gli incrementi della velocità di crociera in situazioni di basso rischio e difficoltà (basse velocità, grandi distance headways e veicolo di fronte più veloce). A parità di condizioni, alcuni guidatori avevano probabilità più alte di sospendere il sistema premendo il pedale dell'acceleratore. La Figura I.D mostra l'impatto di variazioni nelle variabili esplicative sulle probabilità incondizionate di scelta dello stato del sistema ACC e sull'entità della regolazione della velocità di crociera dell'ACC.

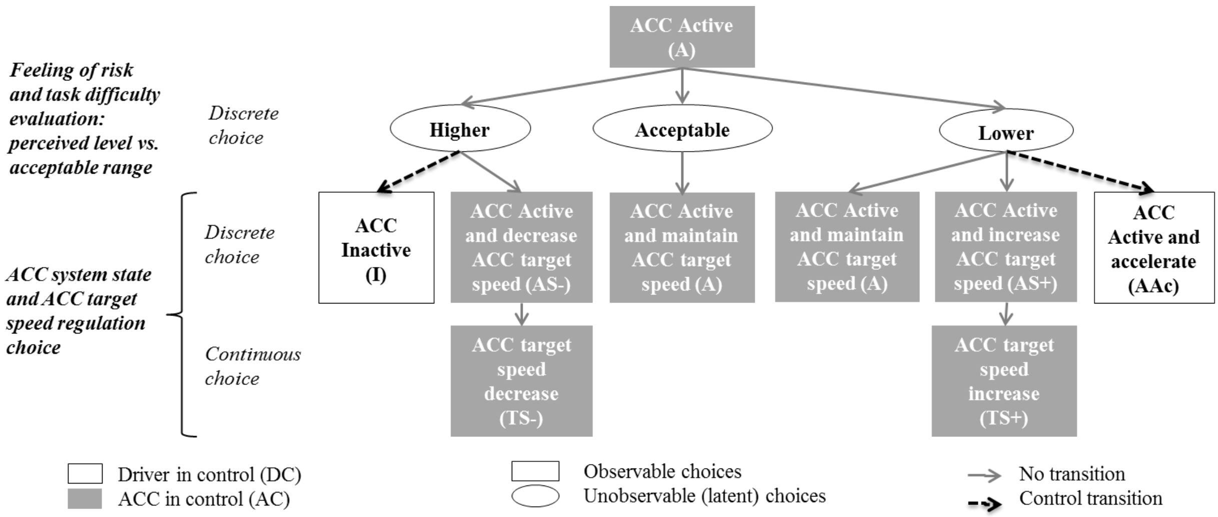


Figura I.C: Modello concettuale per le decisioni del guidatore di riprendere il controllo manuale e di regolare la velocità di crociera con il full-range ACC.

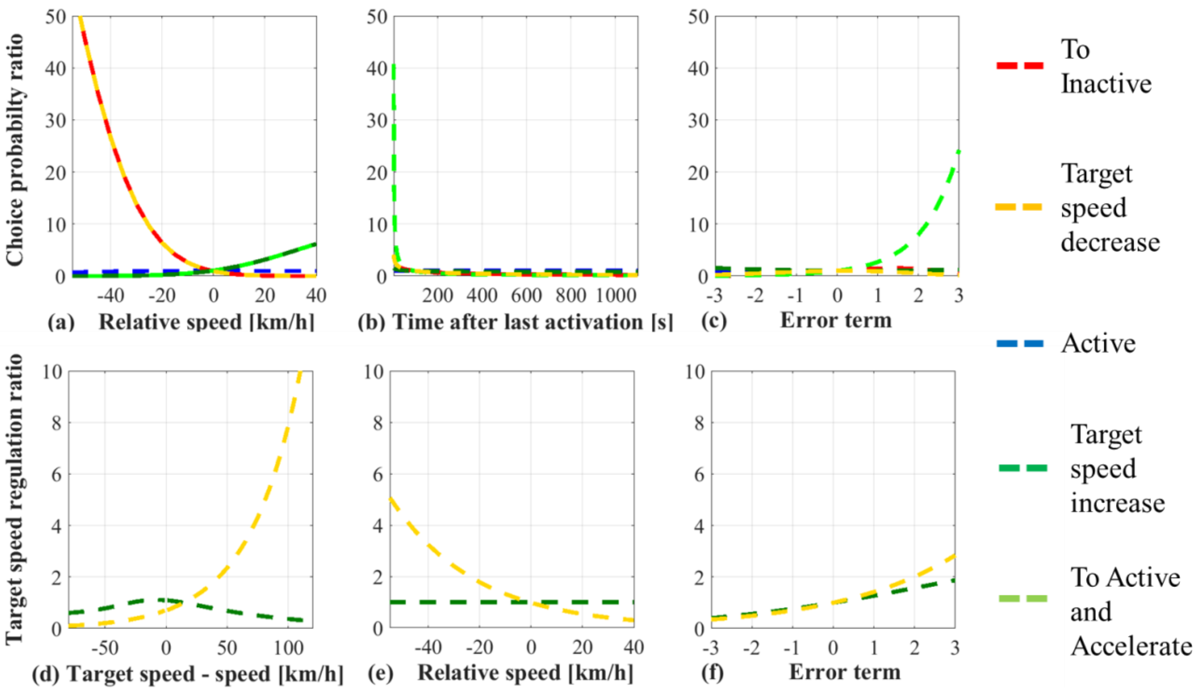


Figura I.D: Effetto di (a) velocità relativa, (b) tempo dopo l'ultima attivazione, e (c) errore specifico del guidatore sul rapporto di probabilità di scelta (probabilità prevista divisa per probabilità dell'osservazione di riferimento) degli stati del sistema ACC. Effetto di (d) velocità di crociera - velocità, (e) velocità relativa, e (f) errore specifico del guidatore sul rapporto di regolazione (regolazione della velocità di crociera prevista divisa per regolazione della velocità di crociera dall'osservazione di riferimento) della velocità di crociera dell'ACC.

Capitolo 6 Conclusioni e raccomandazioni

I risultati degli esperimenti con il simulatore di guida e su strada hanno mostrato che le trasizioni di controllo dal full-range ACC alla guida manuale influiscono significativamente sulle caratteristiche del comportamento del guidatore per qualche secondo dopo che è stato ripreso il controllo manuale. Sulla base della conoscenza dell'autore, questo è il primo studio che ha descritto esplicitamente la durata del periodo di transizione e l'entità della variazione corrispondente nelle caratteristiche del comportamento del guidatore dopo che il guidatore ha disattivato o sospeso l'ACC. Da un punto di vista comportamentale, la riduzione (o l'aumento) della velocità dopo aver ripreso il controllo manuale può essere interpretata come una strategia di compensazione per ridurre (o aumentare) la sensazione di rischio e la difficoltà del compito percepite, e l'intervallo di tempo associato come il periodo necessaria per stabilizzare il comportamento di guida dopo il ripristino del controllo manuale (periodo di transizione).

I risultati sottolineano l'importanza di sviluppare modelli matematici che descrivono la risposta del conducente con l'ACC (*car-following models*) e che possono essere implementati in una simulazione microscopica del flusso di traffico. Studi futuri potrebbero sviluppare un car-following model che descriva esplicitamente adattamenti nelle caratteristiche del comportamento del guidatore durante le transizioni di controllo. In questo modello, l'accelerazione del veicolo può essere specificata come somma di due termini, il primo per rappresentare regolare comportamento di car-following e il secondo per rappresentare effetti di adattamento. Implementando questo modello avanzato di car-following in una simulazione microscopica del flusso del traffico, si potrebbe analizzare l'impatto delle transizioni di controllo sull'efficienza del traffico.

Le decisioni dei guidatori di riprendere il controllo manuale e di regolare la velocità di crociera con il full-range ACC possono essere interpretate in base alla teoria di allostasi del rischio. Questo studio è uno dei primi tentativi di sviluppare un modello che spiega l'interazione fra il guidatore e il sistema di assistenza alla guida a livello operativo sulla base di teorie sviluppate nel campo della psicologia del guidatore. L'interpretazione proposta è supportata dai risultati sperimentali nei modelli di scelta e dalle caratteristiche del comportamento del guidatore dopo la ripresa del controllo manuale. La teoria di allostasi del rischio contribuisce a far luce sul processo decisionale dei guidatori. Questi risultati sottolineano l'importanza di incorporare meccanismi comportamentali di guida realistici nei modelli di comportamento del guidatore.

Il modello di scelta che prevede le transizioni di controllo e le regolazioni della velocità di crociera con il full-range ACC è implementabile in modelli microscopici di flusso del traffico. Sulla base della conoscenza dell'autore, questo è il primo modello che prevede sia le transizioni di controllo sia le regolazioni della velocità di crociera con il full-range ACC sulla base di dati sperimentali. Poiché la struttura del modello è generica, può essere applicata per prevedere il processo decisionale del guidatore a livello operativo con altri sistemi di assistenza alla guida. Il modello può essere implementato in una simulazione microscopica per valutare l'impatto dell'ACC sull'efficienza e la sicurezza del flusso di traffico, rappresentando le transizioni di controllo e le regolazioni della velocità di crociera. Il modello può essere utilizzato anche nei sistemi di assistenza alla guida per identificare le situazioni in cui è probabile che i conducenti riprendano il controllo manuale.

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Curriculum Vitae

Silvia Francesca Varotto was born on December, 26th 1989 in Latisana (Italy). In 2008, she received a scientific high school diploma with final grade 100/100 from Liceo Scientifico XXV Aprile, Portogruaro (Italy). From 2008 to 2013, she studied Civil Engineering, specialization in Transportation at the University of Trieste (Italy). She received both her Bachelor (2011) and her Master (2013) with final grade 110/110 cum Laude. During her studies in Trieste, she was awarded a scholarship for the best students in Engineering four times and received a prize for the best Bachelor thesis in Engineering. In 2013, she received an Erasmus Placement scholarship and carried out her Master Thesis in Discrete Choice Analysis applied to Transportation at École Polytechnique Fédérale de Lausanne (Switzerland).

In January 2014, Silvia joined the Transport and Planning Department of Delft University of Technology as a Marie Curie Fellow in the project “HFAuto: Human Factors of Automated Driving”. This training experience provided her with a unique multidisciplinary background, comprising empirical research and mathematical modelling of driver behaviour in transportation. Her PhD research focused on developing an empirically underpinned driver behaviour model that accounts for control transitions between ACC and manual driving. She was visiting researcher at the Universität de Bundeswehr München and at BMW group in Munich (Germany) in 2015 and at Technion Israel Institute of Technology in Haifa (Israel) in 2016. She was a member of the local organising committee of the Road Safety and Simulation International Conference (RSS) 2017. She received the best presentation award at the Transportation Research Board (TRB) Workshop on Doctoral Research in Transportation Modelling 2018. During her doctoral studies, she assisted in teaching of master courses (Traffic Flow Theory and Simulations course and Intelligent Vehicles course) and in supervising master students in projects focusing on the analysis of driver behaviour data. She has served as referee for international conferences (TRB, IEEE ITSC, IEEE MT-ITS, RSS, hEART) and journals (Transportmetrica A: Transport Science and IEEE Transactions on Intelligent Transportation Systems).

In June 2018, Silvia joined the SWOV Institute for Road Safety Research in The Hague (the Netherlands), where she currently works as a researcher. Her main research interests are mathematical modelling of decision making using econometrics methods, incorporating human factors into microscopic traffic flow models, and analysing the impact of cutting-edge technologies on the behaviour of different classes of road users.

Journal papers

1. Zhang, B., De Winter, J., **Varotto, S.F.,** Happee, R., Martens, M., *under review*. Determinants of take-over time from automated driving: a meta-analysis of 93 studies. *Transportation Research Part F: Traffic Psychology and Behaviour*.
2. **Varotto, S.F.,** Farah, H., Bogenberger, K., Van Arem, B., Hoogendoorn, S.P., *under review*. Adaptations in driver behaviour characteristics during control transitions from full-range Adaptive Cruise Control to manual driving: an on-road study. *Transportmetrica A: Transport Science.*
3. **Varotto, S.F.,** Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2018. Modelling decisions of control transitions and target speed regulations in full-range Adaptive Cruise Control based on Risk Allostasis Theory. *Transportation Research Part B: Methodological* 117, 318-341.
4. **Varotto, S.F.,** Glerum, A., Stathopoulos, A., Bierlaire, M., Longo, G., 2017. Mitigating the impact of errors in travel time reporting on mode choice modelling. *Journal of Transport Geography* 62, 236–246.
5. **Varotto, S.F.,** Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2017. Resuming manual control or not? Modelling choices of control transitions in full-range adaptive cruise control. *Transportation Research Record: Journal of Transportation Research Board* 2622, 38-47.
6. **Varotto, S.F.,** Hoogendoorn, R.G., Van Arem, B., Hoogendoorn, S.P., 2015. Empirical longitudinal driving behaviour in authority transitions between adaptive cruise control and manual driving. *Transportation Research Record: Journal of Transportation Research Board* 2489, 105-114.

Peer-reviewed conference papers

1. **Varotto, S.F.,** Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2018. Continuous-discrete choices of control transitions and speed regulations in full-range Adaptive Cruise Control. Transportation Research Board 97th Annual Meeting, Washington, D.C., paper 18-03199 (reviewed by AHB45 Traffic Flow Theory and Characteristics Committee).
2. **Varotto, S.F.,** Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2017. Acceptable or not? Multi-level choices of control transitions and speed regulations in full-range Adaptive Cruise Control. Road Safety and Simulation International Conference, The Hague, NL.
3. **Varotto, S.F.,** Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2017. Resuming manual control or not? Modelling choices of control transitions in full-range adaptive cruise control. Transportation Research Board 96th Annual Meeting, Washington, D.C., paper 17-02890 (reviewed by AHB45 Traffic Flow Theory and Characteristics Committee).

4. **Varotto, S.F.,** Hoogendoorn, R.G., Van Arem, B., Hoogendoorn, S.P., 2015. Empirical longitudinal driving behaviour in case of authority transitions between adaptive cruise control and manual driving. Transportation Research Board 94th Annual Meeting, Washington, D.C., paper 15-3077 (reviewed by AHB30 Vehicle-Highway Automation Committee).
5. Hoogendoorn, R.G., **Varotto, S.F.,** Bogenberger, K., Hagenzieker, M., Van Arem, B., 2015. Towards Optimal Traffic Safety on Freeways through Automated Vehicles and Traffic System Complexity Estimation. Transportation Research Board 94th Annual Meeting, Washington, D.C., paper 15-1978 (reviewed by AHB45 Traffic Flow Theory and Characteristics Committee).
6. **Varotto, S.F.,** Glerum, A., Stathopoulos, A., Bierlaire, M., Longo, G., 2015. Modelling travel time perception in transport mode choices. Transportation Research Board 94th Annual Meeting, Washington, D.C., paper 15-2045 (reviewed by ADB40 Transportation Demand Forecasting Committee).
7. **Varotto, S.F.,** Hoogendoorn, R.G., Van Arem, B., Hoogendoorn, S.P., 2014. Human factors of automated driving: Predicting the effects of authority transitions on traffic flow efficiency. 2nd TRAIL Internal Congress, Delft, The Netherlands.
8. **Varotto, S.F.,** Glerum, A., Stathopoulos, A., Bierlaire, M., 2014. Modelling travel time perception in transport mode choices. Proceedings of the 14th Swiss Transport Research Conference, Ascona, Switzerland.

Conference presentations

1. **Varotto, S.F.,** 2018. Driver behaviour in control transitions between adaptive cruise control and manual driving: empirics and models. Workshop on Doctoral Research in Transportation Modelling and Travel Behaviour, Transportation Research Board 97th Annual Meeting, Washington, D.C. **(Best presentation award).**
2. **Varotto, S.F.,** Farah, Toledo, T., H., Van Arem, B., Hoogendoorn, S.P., 2017. Acceptable or not? Modelling choices of control transitions and speed regulations in full-range Adaptive Cruise Control. Presentation at the 4th TRAIL Internal Congress, Utrecht, The Netherlands.
3. **Varotto, S.F.,** Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2017. Modelling multi-level choices of control transitions in full-range adaptive cruise control. Presentation at hEART 2017 – 6th Symposium of the European Association for Research in Transportation, Technion Israel Institute of Technology, Israel.
4. **Varotto, S.F.,** Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2017. Modelling choices of control transitions and speed regulations in full-range adaptive cruise control. Presentation at 12th Workshop on Discrete Choice models, École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland.
5. **Varotto, S.F.,** Farah, H., Bogenberger, K., Van Arem, B., Hoogendoorn, S.P., 2017. Temporal evolution of driving behaviour characteristics when resuming manual

control. 8th International Conference on Applied Human Factors and Ergonomics, Los Angeles, CA.

6. **Varotto, S.F.,** Farah, H., Van Arem, B., Hoogendoorn, S.P., 2016. Modelling driver behaviour in control transition between adaptive cruise control and manual driving. Presentation at the 3rd TRAIL Internal Congress, Utrecht, The Netherlands.
7. **Varotto, S.F.,** Farah, H., Van Arem, B., Hoogendoorn, S.P., 2016. Empirical analysis of driving behaviour in authority transitions between adaptive cruise control and manual driving. Presentation at hEART 2016 – 5th Symposium of the European Association for Research in Transportation, Delft University of Technology, The Netherlands.
8. **Varotto, S.F.,** Farah, H., Toledo, T., Van Arem, B., Hoogendoorn, S.P., 2016. A framework for modelling driving behaviour in authority transitions between adaptive cruise control and manual driving. Presentation at the ITS European Congress 2016, Glasgow, United Kingdom.
9. **Varotto, S.F.,** Farah, H., Van Arem, B., Hoogendoorn, S.P., 2015. Empirical car-following and lane-changing driving behaviour in case of authority transitions between adaptive cruise control and manual driving. Presentation at the 2nd TRAIL-Beta PhD Conference, Utrecht, The Netherlands.
10. **Varotto, S.F.,** Farah, H., Hoogendoorn, R.G., Van Arem, B., Hoogendoorn, S.P., De Winter, J. C. F., 2015. Effects of automated driving on traffic flow efficiency: Challenges and recent developments. Presentation at the 6th International Conference on Applied Human Factors and Ergonomics. Las Vegas, NV.
11. **Varotto, S.F.,** Farah, H., Hoogendoorn, R.G., Van Arem, B., Hoogendoorn, S.P., 2015. Driving behaviour in case of authority transitions between Adaptive Cruise Control and manual driving. Presentation at the 18th Euro Working Group on Transportation (EWGT), Delft, The Netherlands.
12. **Varotto, S.F.,** Hoogendoorn, R.G., Van Arem, B., Hoogendoorn, S.P., 2014. Effects of authority transitions between adaptive cruise control and manual driving on traffic flow efficiency. Presentation at hEART 2014 - 3rd Symposium of the European Association for Research in Transportation, University of Leeds, United Kingdom.
13. **Varotto, S.F.,** Hoogendoorn, R.G., Van Arem, B., 2014. Human Factors of automated driving: Towards predicting the effects of authority transitions on traffic flow efficiency. Poster presented at the Automated Vehicles Symposium 2014, San Francisco, CA.
14. **Varotto, S.F.,** Glerum, A., Stathopoulos, A., Bierlaire, M., 2013. Modelling travel time perception: an integrated choice and latent variable approach. Presentation at 8th Workshop on Discrete Choice models, École Polytechnique Fédérale de Lausanne, Lausanne, Switzerland.

Scientific meetings

1. ITS seminar series, University of Leeds, Leeds, UK, Feb. 26-27, 2018 (*presenter*, invited by N. Merat).
2. 22nd International Symposium for Transportation and Traffic Theory (ISTTT), Chicago, US, Jul. 24-26, 2017.
3. HF-Auto Progress Meeting and Workshop, Chalmers University of Technology and Swedish National Road and Transport Research Institute (VTI), Göteborg, Sweden, Sept. 5—9, 2016 (*presenter*, hosted by M. Dozza and J. Andersson).
4. HF-Auto Progress Meeting and Workshop, The French Insitute of Science and Technology for Transport, Development and Networks (IFSTTAR), Lyon, France, Apr. 4—8, 2016 (*presenter*, hosted by T. Bellet and M. Bruyas).
5. HF-Auto Progress Meeting and Workshop, University of Southampton, Southampton, United Kingdom, Sept. 21—25, 2015 (*presenter*, hosted by N. Stanton).
6. HF-Auto Progress Meeting and Workshop, Technische Universität München, München, Germany, Jan. 19—23, 2015 (*presenter*, hosted by K. Bengler).
7. ITS Workshop, Delft University of Technology, Delft, The Netherlands, Oct. 29, 2014 (*presenter*, invited by M. Keyvan-Ekbatani).
8. Field experiment on Cooperative Advanced Driver Assistance Systems, University of Luxembourg, Luxembourg City, Luxembourg, Sept. 25-26, 2014 (*visiting researcher*, invited by F. Viti).
9. COST Action TU1102, Development of ARTS Demonstrator, University of Newcastle, Newcastle, UK, Aug. 31–Sept. 4, 2014 (*visiting researcher*, hosted by M. Bell and F. Galatioto).
10. COST Action TU1102, WG3 Meeting and ARTS Demonstrator workshop, University of Enna Kore, Enna, Italy, Jun. 25–26, 2014 (*presenter*, hosted by T. Campisi and F. Galatioto).
11. HF-Auto Kick-off Meeting and Workshop, Delft University of Technology, Delft, The Netherlands, Jun. 10-13, 2014 (*presenter*, hosted by R. Happee).
12. 13th Swiss Transportation Research Conference (STRC), Ascona, Switzerland, Apr. 24-26, 2013.

Technical reports

1. **Varotto, S.F.,** Solís-Marcos, I., Zhang, B., De Winter, J. C. F., Happee, R., 2017. Predicting real world effects of automation (Report No. HFAuto D4.1).
2. Happee, R., **Varotto, S.F.,** Lu, Z., Cabrall, C., Kyriakidis, M., Petermeijer, S. M., Goncalves, J., 2017. Second specification of the foreseen modes of automated driving, studied in the HFAuto project and their potential conflict with European regulations (Report No. HFAuto D5.2).

Outreach

1. Human factors of automated driving research highlights, AutoMotive Week, Helmond, The Netherlands, Mar. 31, 2017 (*presenter* and *co-organizer* with B. Zhang).
2. Human factors of automated driving, Dig-it! Research Exhibition, Delft University of Technology, Delft, The Netherlands, Nov. 11, 2014 (*presenter*, organized by M. Kyriakidis).

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Yuan, K., *Capacity Drop on Freeways: Traffic dynamics, theory and Modeling*, T2016/24, December 2016, TRAIL Thesis Series, the Netherlands

Li, S., *Coordinated Planning of Inland Vessels for Large Seaports*, T2016/23, December 2016, TRAIL Thesis Series, the Netherlands

Berg, M. van den, *The Influence of Herding on Departure Choice in Case of Evacuation: Design and analysis of a serious gaming experimental set-up*, T2016/22, December 2016, TRAIL Thesis Series, the Netherlands