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Adaptations in driver behaviour characteristics during control transitions from full-range Adaptive Cruise Control to manual driving: an on-road study

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ABSTRACT

Adaptive Cruise Control (ACC) can reduce traffic congestion and accidents. In dense traffic flow conditions and when changing lanes, drivers prefer to deactivate the ACC. These *control transitions* between automation and manual driving could impact driver behaviour characteristics. However, few studies have analysed the magnitude and duration of these adaptations. This research aims at quantifying the adaptations in speed, acceleration, distance headway and relative speed when drivers resume manual control. We collected driver behaviour data in an on-road experiment with full-range ACC during peak hours in Munich. We analysed these data using linear mixed-effects models to identify statistically significant changes in driver behaviour characteristics after drivers resumed manual control (*transition period*). The results reveal that the speed decreased significantly after the system was deactivated and it increased significantly after the system was overruled by pressing the gas pedal. These adaptations might have a substantial impact on traffic efficiency and safety.

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Control transitions; transition period; Adaptive Cruise Control; on-road experiment; driver behaviour; linear mixed-effects models

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, van Arem, and Hoogendoorn 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

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it keeps a target speed and time headway (Martens and Jenssen 2012). On-road experiments (NHTSA 2005; Alkim, Bootsma, and Hoogendoorn 2007; Malta et al. 2012; 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 (NHTSA 2005; Alkim, Bootsma, and Hoogendoorn 2007; Malta et al. 2012; 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, Bootsma, and Hoogendoorn 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) categorised 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 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 Minderhoud 2008; Pauwelussen and Feenstra 2010) (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 Minderhoud 2008; Pauwelussen and Feenstra 2010). 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, 2018), changes lane (Pereira, Beggiato, and Petzoldt 2015), and exits the freeway (Pereira, Beggiato, and Petzoldt 2015; Varotto et al. 2017, 2018). These systems are overruled by pressing the gas pedal a few seconds after activation and when the vehicle decelerates (Varotto et al. 2017, 2018). 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 (Van Arem, De Vos, and Vanderschuren 1997; Klunder, Li, and Minderhoud 2009; Xiao, Wang, and van Arem 2017; Xiao et al. 2018) 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 (Saifuzzaman and Zheng 2014; Hamdar, Mahmassani, and Treiber 2015; Paschalidis, Choudhury, and Hess 2018, 2019a; Van Lint and Calvert 2018; Hamdar et al. 2019; Manjunatha and Elefteriadou 2019; McDonald et al. 2019).

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. This data collection method allows to analyse driving behaviour in real traffic with a high degree of external validity, controlling for confounding factors (e.g. road design, traffic flow conditions, time of the day and weather) and increasing the exposure to the conditions under investigation (e.g. congestion) (for a comprehensive review on on-road data collection methods, see Carsten, Kircher, and Jamson [2013]).

The paper is organised as follows. The next section provides an overview on adaptations in longitudinal driver behaviour when manual control is resumed and on limitations of data analysis methods for repeated measures. The research gaps and the research hypotheses are presented at the end of this section. The following section describes the specifications of the ACC system, the experimental design, and the data collection. Next, the dataset, the data processing, and the exploratory data analysis are presented. The following section describes the statistical analysis methods capturing adaptations in driver behaviour characteristics and the estimation results. After that, the driver behaviour characteristics of individual drivers during control transitions and during manual driving are compared. The last section discusses the relevance of these findings for the development of new driving assistance systems and microscopic traffic flow models.

Literature review

This section 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, we define adaptions 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]). We conclude the literature review by defining the research gaps and formulating the research hypotheses that are tested in this study.

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 (NHTSA 2005; Alkim, Bootsma, and Hoogendoorn 2007; 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 Minderhoud 2008; Pauwelussen and Feenstra 2010) 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, Beggiato, and Petzoldt 2015; Varotto et al. 2017, 2018). 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 Minderhoud 2008; Pauwelussen and Feenstra 2010) 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. To control for these factors, a more in-depth analysis is needed.

The time needed by drivers to stabilise 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, we need a flexible data analysis technique capturing variations between subjects and correlations between observations over time for the same subject.

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 (Peng, Boyle, and Lee 2014; Peng and Boyle 2015; Oviedo-Trespalacios et al. 2017; Wang et al. 2017; Geden, Staicu, and Feng 2018; Saad, Abdel-Aty, and Lee 2018; Albert 2019). 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 that 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 that are captured in the model (Quené and van den Bergh 2004). We conclude that linear mixed-effects models are a suitable data analysis technique to capture adaptations in driver behaviour characteristics over time.

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 Minderhoud 2008; Pauwelussen and Feenstra 2010). 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, we need a flexible data analysis technique. 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. We are particularly interested in analysing driver behaviour characteristics in dense traffic because describing accurately driving behaviour in these conditions is more relevant 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. Descriptive statistics are used 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. Linear mixed-effects models are proposed 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. The results reveal the duration and magnitude of the transition periods for each type of control transition. Finally, drivers' responses during the transition periods and during manual driving in similar traffic situations are compared.

Experimental set-up

In this section, we describe the characteristics of the ACC system and the data collection systems available, the experimental design, the test route and the data collection. A reduced description of the experiment has been presented in a previous study analysing the main factors that influence drivers' decisions to resume manual control (Varotto et al. 2017).

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 with 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. In this paper, we will focus 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 1 presents possible DIDC and DIAC

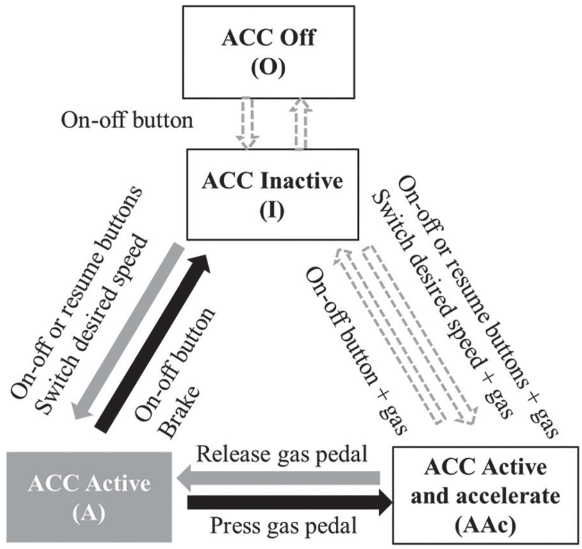
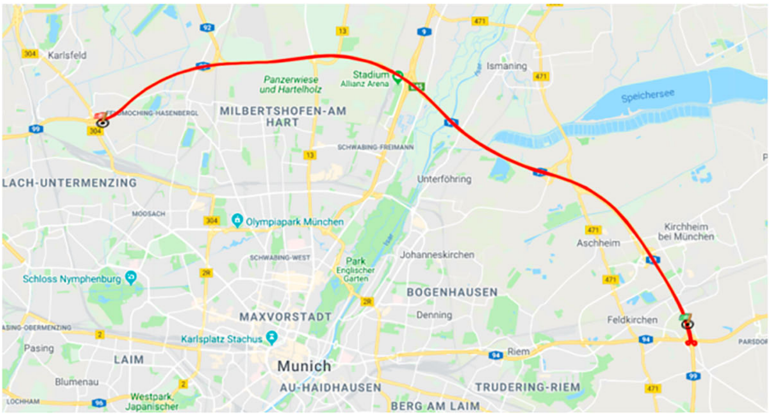


Figure 1. Control and state transitions between ACC system states that can be initiated by drivers.
Note: White boxes denote system states in which drivers are in control, while grey boxes states in which ACC is in control. Solid arrows indicate control transitions, while dashed arrows state transitions. Grey solid arrows define 'Driver Initiates transition, and Automation in Control after' (DIAC), black solid arrows 'Driver Initiates transition, and Driver in Control after' (DIDC). An early version of the figure was presented in Varotto et al. (2017).

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 the paper. 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 s (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).

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



(a)

(b)

Figure 2. (a) Map of the test route on the A99 in Munich (Google Maps Viewed May 17, 2018) and (b) picture of the basic freeway section.

Note: An early version of the figure was presented in Varotto et al. (2017).

vehicle). In addition, lane-specific mean speeds and counts were recorded by dual inductive loop detectors at one minute intervals.

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 2(a)) mostly composed of three lanes per direction (Figure 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.

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*. During the training session on the first freeway segment, participants tested the ACC 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.

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. The weather conditions (clear sky or light clouds) and the lightening conditions (daylight) were favourable. 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. All participants reported that they had understood the functioning of the ACC system during the training session and that they were confident of participating in the experiment. The duration of test drive was between 45 and 90 min based on the traffic flow conditions.

Datasets used

In this section, we briefly discuss the different data sets (CAN-bus and loop detector data) that were collected during the experiment and analysed in this study.

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 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, we noted 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 paper will analyse only the transitions initiated by drivers.

Table 1. Number and percentage of transitions to *Inactive* (A to I) and to *Active and accelerate* (A to AAc) based on initiation mode.

		Transition initiation			
		Driver		ACC	
Transition type	*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%)	–	

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 and 2250 m ($M = 1273$ m, SD $= 441$ m) as presented in the road network in Figure 3(a) and 3(c). Two detectors did not record any data, all detectors malfunctioned for 24 h 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 synchronised (manually). Figure 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(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(d)). At the end of the third freeway segment (Figure 3(b)), the ACC system deactivated automatically after the vehicle stood still for more than 3 s 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.

Data processing

To gain insight into driver behaviour during control transitions, we analysed the longitudinal driver behaviour characteristics (speed, acceleration, distance headway, and relative

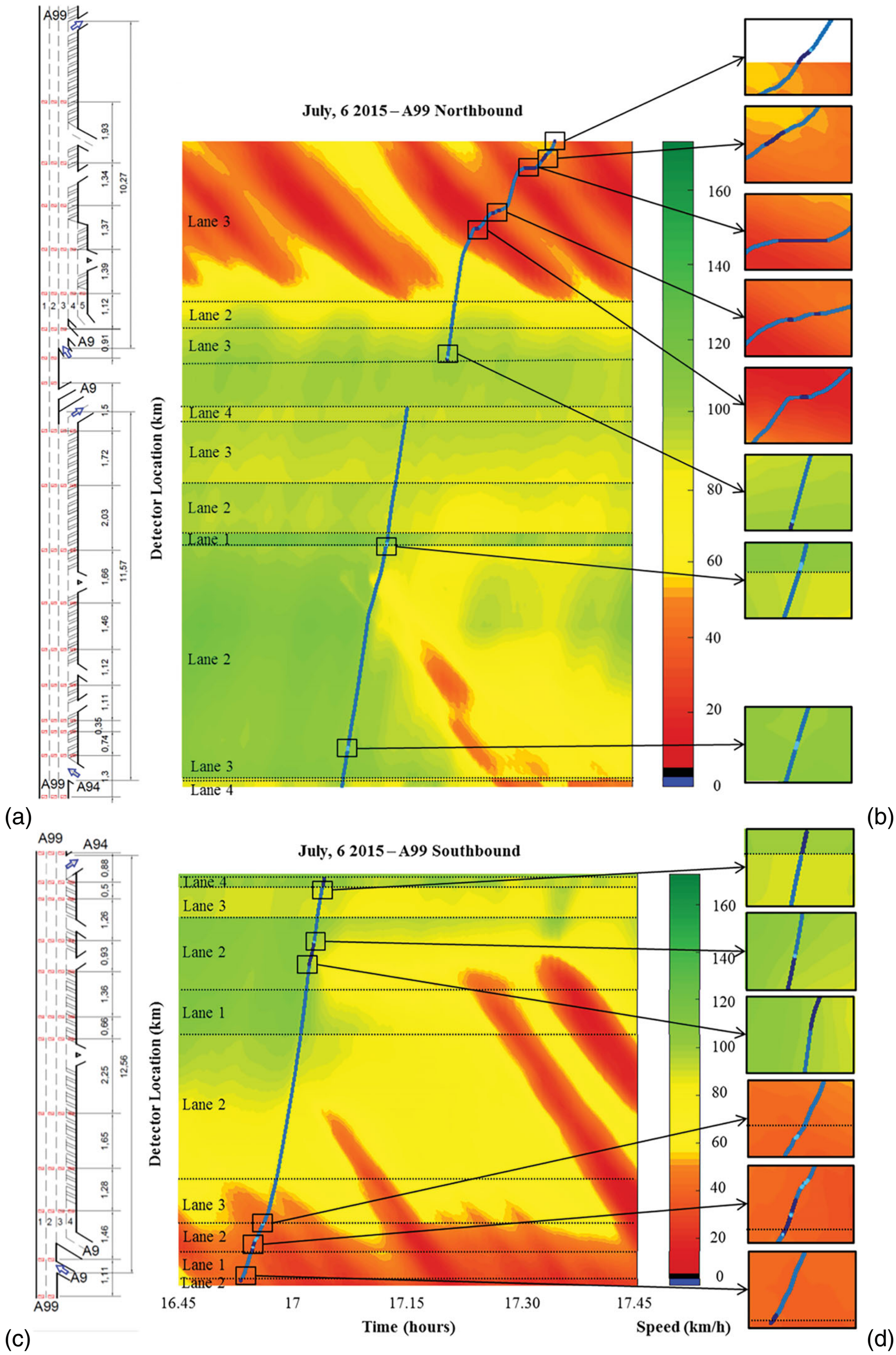


Figure 3. Road network of the test site: (a) northbound A99, and (c) southbound A99. (b, d) Trajectory of a test vehicle (blue line) and time-space speed contour plots of the lane in which the vehicle was in during the experiment.

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*.

speed) 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 (2017). 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.

Data analysis

In this paper, we analyse 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 comprises 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

Table 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%

during control transitions. In the remainder of this section, we explore, at an aggregate level, the relationships existing between driver behaviour characteristics in control transitions and ACC system states, average traffic density conditions, and time period before and after transferring control.

Table 2 shows the percentages of time in each system state in the 10-s intervals before and after the transitions. These percentages indicate that other transitions were initiated in the 10-s intervals. Sometimes the system was active in the 10-s interval after the transition to I, meaning that the ACC was deactivated for less than 10 s. The system was AAc for a limited percentage of time after the transition to AAc, meaning that the ACC was overruled for a few seconds only. These results support our hypothesis that it is necessary to control for the system state when analysing the driver behaviour characteristics during control transitions.

The mean and standard deviation (values aggregated over 10-s intervals) of speed, acceleration, distance headway and relative speed were calculated for each density level in the 10-s interval before and 10-s after the transitions (Appendix A, Table A1). Paired samples *t*-tests were performed to check whether the differences in these mean values were significant (Appendix A, Table A1). Figure 4 presents 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 (Appendix A, Table A1): the mean speeds and accelerations decreased significantly, the standard deviation of speeds and accelerations increased significantly, and the mean distance headways decreased significantly. Figure 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 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 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 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

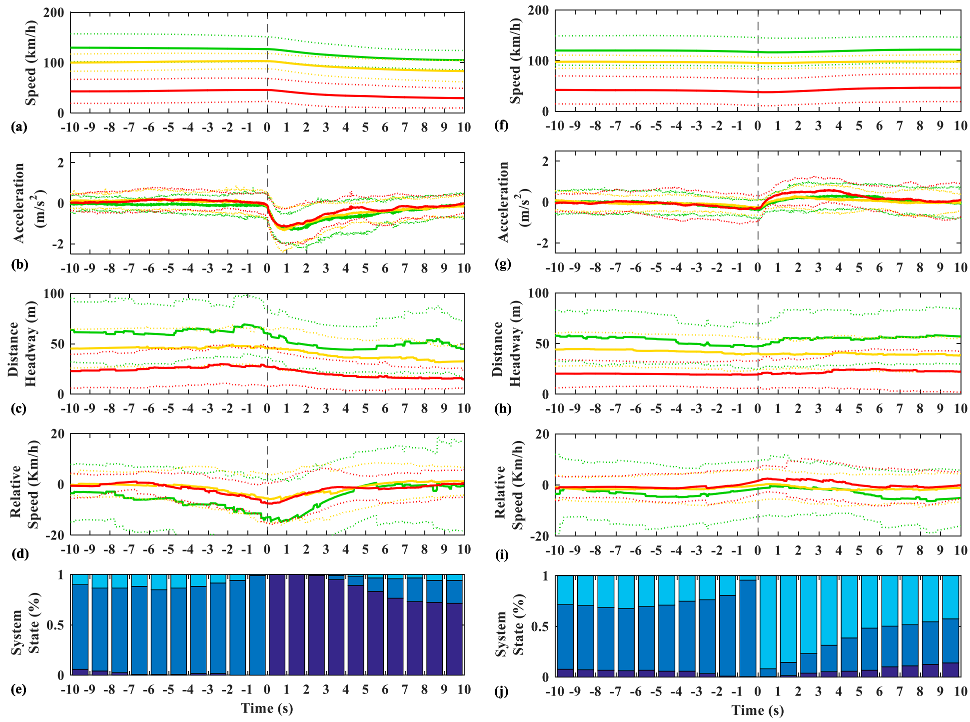


Figure 4. Transitions to *Inactive* (A to I, a-e) and to *Active and accelerate* (A to AAc, f-j): mean (solid line) and standard deviation (dashed line) of (a, f) speed, (b, g) acceleration, (c, h) distance headway and (d, i) relative speed calculated as a function of time in the interval 10 s before (—10, 0) and 10 s after (0, 10) the instant when the transition is initiated (dashed black line); (e, 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, j), dark blue bars represent *Inactive*, blue represent *Active*, and light blue *Active and accelerate*.

at medium and high densities, and the standard deviations of accelerations increased significantly at medium densities (Appendix A, Table A1). Figure 4(f-g) 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 4(h) 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 4(i) shows that the mean relative speeds increased before the transition and decreased afterwards. Figure 4(j) 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 during 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, we will examine adaptation effects in driver behaviour characteristics 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).

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 5). To analyse the impact of several within-subjects factors simultaneously (e.g. time period, traffic density, ACC system state) on the driver behaviour characteristics capturing between-subjects variations and correlations between observations over time for the same subject, we estimated linear mixed-effects models for repeated measures containing fixed and random effects. 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).

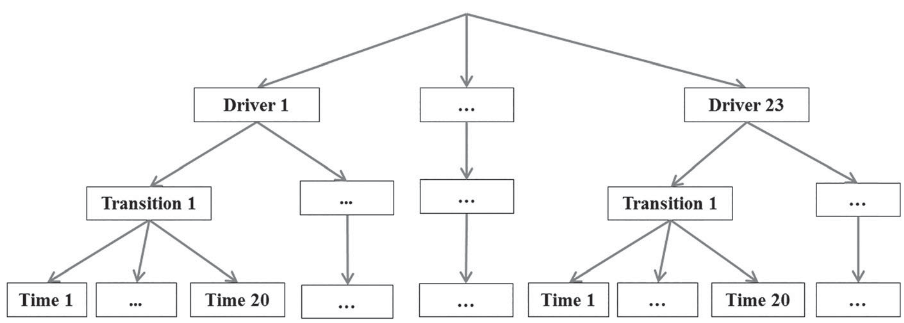


Figure 5. Multi-level structure of the driver behaviour data.

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 in each level and 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* ($t = 1, \ldots, 20$) are given by eq. (1):

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

where α is the intercept (mean); β are the parameters associated with each level of the categorical explanatory variables; $\mathrm{Time}_{\mathrm{Tr}}(\mathrm{t})$ is a dummy variable denoting the time t ($t = 1, \ldots, 20$); $\mathrm{SystSta}^{i}_{\mathrm{Tr}}(t)$ 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 $i = 1,2,3$; $\mathrm{Dens}^{k}_{\mathrm{Tr}}$ 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 $\vartheta_n \sim N(0,1)$; σ is the parameter (between observations variance) associated with the observation-specific error term (residual) $\varepsilon_{n,\mathrm{Tr}}(t)$,

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

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 normalised 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 $\mathbf{\Lambda}_{\boldsymbol{n},\mathbf{Tr}}$ is specified as a first-order autoregressive moving-average ARMA(1,1) (Pinheiro and Bates 2000; Box, Jenkins, and Reinsel 2013). 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.

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 stabilise 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.

Estimation results

The tests of fixed effects and of covariance parameters of the linear mixed-effects models for each dependent variable and transition type are reported in Appendix A, Table A2. Results statistically significant at the 95% confidence level are discussed in the next sections. 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

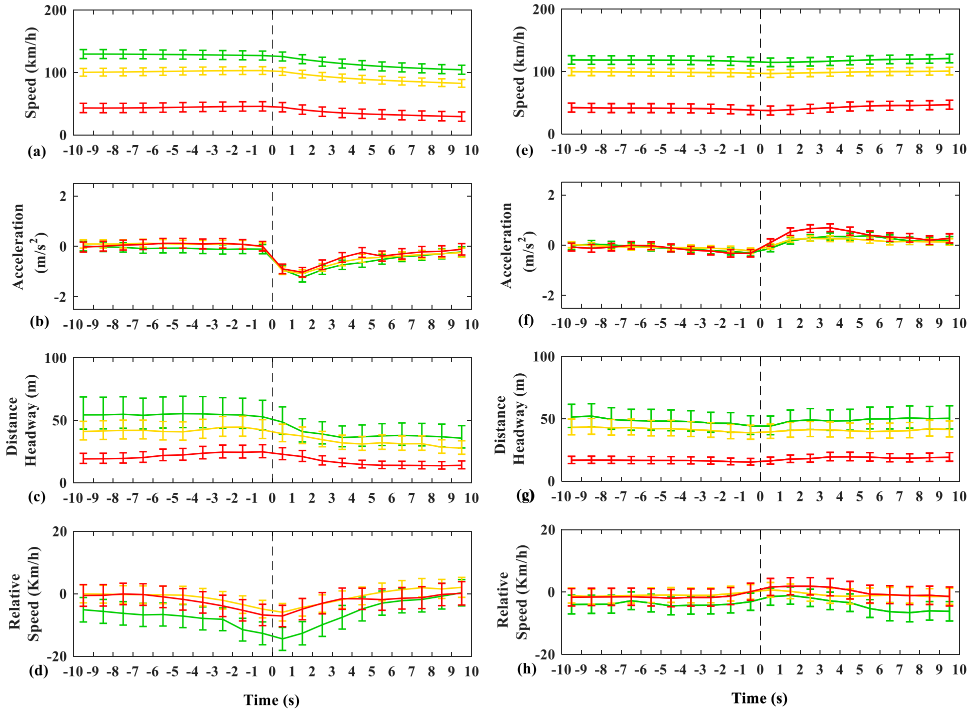


Figure 6. Transitions to *Inactive* (*A to I*, a-d) and to *Active and accelerate* (*A to AAc*, e-h): estimated marginal means (solid line) and 95% confidence intervals of the mean estimates (error bars) of (a, e) speed, (b, f) acceleration, (c, g) distance headway and (d, h) relative speed calculated 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).

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 the previous section. 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 6 shows 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 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.

Table 3. 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*).

		I (after A to I)				AAc (after A to AAc)			
DBC	*Density level*	*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
	Medium	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
Acceleration (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				
	Medium	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
	Medium	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
	Medium	NS	NS	NS	NS	NS	NS	NS	NS
	High	NS	NS	NS	NS	NS	NS	NS	NS

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

Adaptations in transition to Inactive (DIDC)

The linear mixed-effects models (Appendix A, Table A2) 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: $p = 0.056$), 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 6(a-d) show the profiles of the mean driver behaviour characteristics, which are consistent with the empirical findings in Figure 4(a-d). 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: $p < 0.0005$), meaning that the speed decreases significantly. This duration indicates the time drivers need to stabilise the speed (transition period, Table 3). The acceleration was significantly higher 0–1 s after the transition than 1–2 s after ($p < 0.0005$) and in each second in the interval 1–4 s the acceleration was significantly lower than in the following observations (1–2 s: $p < 0.0005$; 2–3 s: $p < 0.0005$; 3–4 s: $p = 0.009$), 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: $p < 0.0005$; 1–2 s: $p < 0.0005$; 2–3 s: $p = 0.001$), 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: $p < 0.0005$, 2–3 s: $p = 0.001$), 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.

Adaptations in transition to Active and Accelerate (DIDC)

The linear mixed-effects models (Appendix A, Table A2) 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 6(e-h) show the profiles of the mean driver behaviour characteristics, which are consistent with the empirical results in Figure 4(f-i). 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: $p = 0.014$, 2–3 s to 4–5 s: $p < 0.0005$), 1–3 s after the transition at medium densities (1–2 s: $p < 0.0005$; 2–3 s: $p = 0.011$), and 0–5 s after the transition at high densities (0–1 s: $p = 0.001$; 1–2 s to 3–4 s: $p < 0.0005$; 4–5 s: $p = 0.024$) the speed was significantly lower than in the following observations, meaning that the speed increased significantly. This duration indicates the time drivers need to stabilise the speed (transition period, Table 3). The acceleration was significantly lower 0–1 s after the transition than 1–2 s after ($p < 0.0005$) 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 ($p = 0.006$) and high densities ($p = 0.008$), 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.

Comparison between adaptations in control transitions and manual driving

We compared the driver behaviour characteristics of individual drivers during control transitions and during manual driving to understand if drivers' responses differed in similar traffic situations. This analysis focused on traffic situations in which a leader was detected by the radar (120 m range) and lane changes were not executed within a time interval of 10 s. Observations in manual driving in the 10-s interval before the activation of the ACC system were excluded. Figure 7(a)-(b) show the acceleration of two individual drivers at time $t + 1$ as a response of the relative speed and of the distance headway at time t. Three phases are distinguished: transition period to I, transition period to AAc, and manual driving after resuming control. The duration of the transition period was defined for each traffic density level based on the findings in Table 3. In addition, we selected an equal number of observations during the transition period to I and manual driving when drivers approached a slower leader and during the transition period to AAc and manual driving when drivers approached a faster leader in similar combinations of relative speed and distance headway. Two-sample Kolmogorov–Smirnov tests were used to test whether the distributions

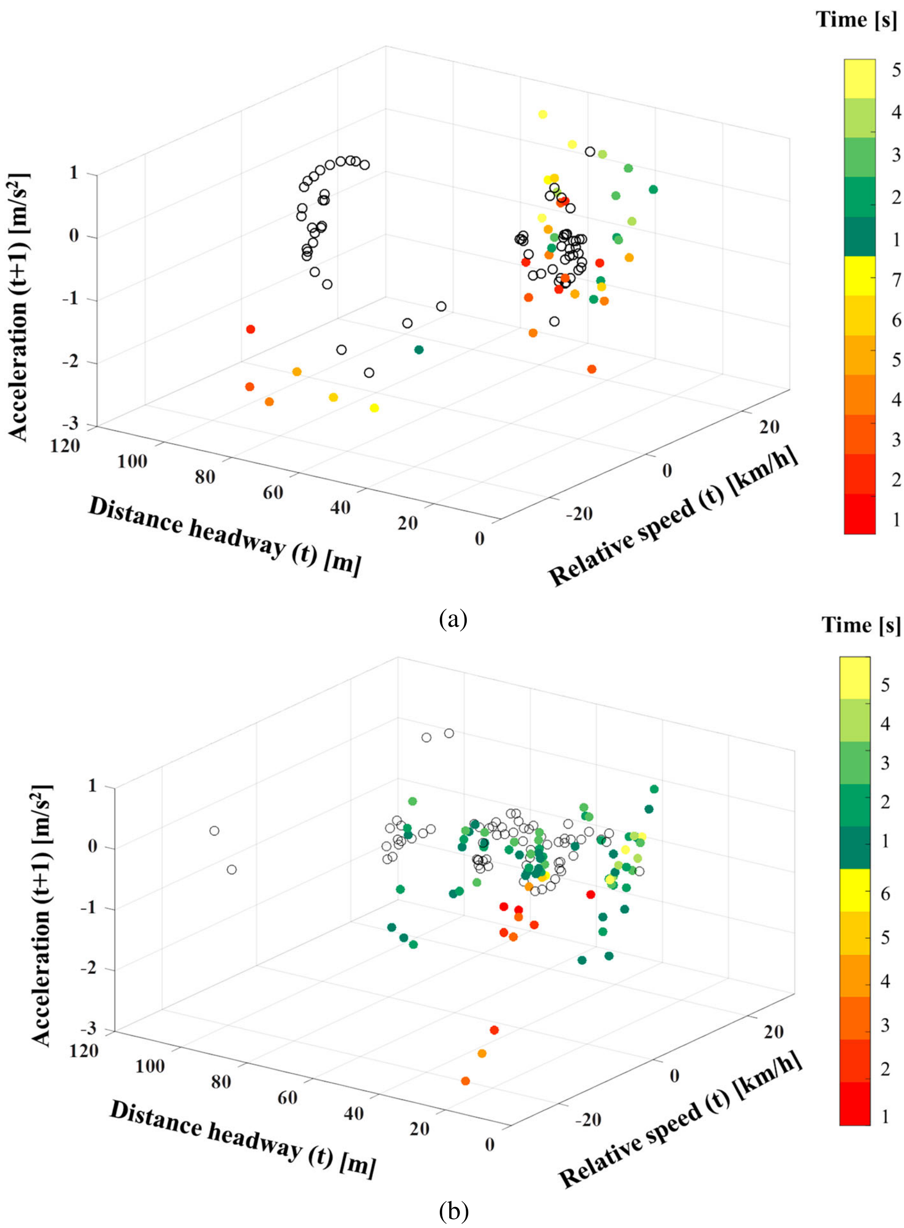


Figure 7. Relative speed, distance headway and acceleration planes for (a) Driver 1 and (b) Driver 2: transition period to *Inactive* (red colour map circles), transition period to *Active and accelerate* (green colour map circles), and manual driving after resuming control (black empty circles).

Note: Each circle corresponds to a 1-s observation. The colour maps indicate the time after the transition.

of relative speed, distance headway and acceleration differed significantly between the two conditions.

Figure 7(a) shows that the driver decelerated more during transitions to I ($M = -1.15$, SD $= 0.832$ m/s^2) than during manual driving ($M = -0.179$, SD $= 0.288$ m/s^2) when approaching a slower leader in similar combinations of relative speed and distance headway ($n = 17$). The two-sample Kolmogorov Smirnov test indicated that the acceleration distributions differed significantly between the two conditions ($p = 0.001$). Clear conclusions for transitions to AAc cannot be drawn due to the limited number of observations available in manual driving when approaching a faster leader. In Figure 7(b), the driver decelerated more when approaching a slower leader during transitions to I ($M = -0.724$, SD $= 0.326$ m/s^2) than in similar situations ($n = 7$) during manual driving ($M = -0.200$, SD $= 0.141$ m/s^2). The acceleration distributions differed significantly between the two conditions ($p = 0.004$). In addition, the driver accelerated more when approaching a faster leader during transitions to AAc ($M = 0.101$, SD $= 0.268$ m/s^2) than in similar situations ($n = 17$) during manual driving ($M = 0.0155$, SD $= 0.279$ m/s^2). However, the acceleration distributions did not differ significantly ($p = 0.673$).

Conclusions and recommendations for 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 authors' 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 recognises 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. Finally, the driver behaviour characteristics of individual drivers during control transitions and during manual driving were compared to understand if drivers' responses differed in similar traffic situations.

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, Beggiato, and Petzoldt 2015), approaching a slower leader (Varotto et al. 2017, 2018), approaching areas of increased lane changes as on-ramps (Varotto et al. 2017, 2018), expecting vehicles cutting-in (Varotto et al. 2017, 2018), and preparing to exit the freeway (Varotto et al. 2017, 2018). The transition period can be interpreted as the duration needed to stabilise 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. These findings are also supported by the comparison with manual driving behaviour. During the transition period, most drivers were more sensitive to the stimulus and responded with larger decelerations when approaching a slower leader.

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, Beggiato, and Petzoldt (2015), when approaching a faster leader (Varotto et al. 2017, 2018) 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. Further research is needed to understand if drivers are more sensitive to the stimulus and respond with larger accelerations during the transition period than in manual driving when approaching a faster leader.

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. During the transition period, drivers are more sensitive to the stimulus than in manual driving and respond with larger decelerations when approaching a slower leader. 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 (Goodrich and Boer 2003; Bifulco et al. 2013). 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 models we developed in previous studies can be implemented into these new systems to identify the situations in which drivers are likely to resume manual control (Varotto et al. 2017, 2018). 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 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, 2018) 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 during control transitions (similar to the advanced car-following models capturing compensation effects at sags by Goni-Ros et al. (2016), driver distraction by Hoogendoorn, Van Arem, and Hoogendoorn (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 (De Winter et al. 2014) can be analysed to shed light on the origin of these adaptation effects in driver behaviour characteristics (Manjunatha et al. 2019; Paschalidis, Choudhury, and Hess 2019a, 2019b). 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).

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Appendix. Data analysis

Table A1. 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 headways	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

Note: The unit of the speed and of the relative speed is km/h, the unit of the acceleration is m/s^2, and the unit of the distance headway is m.

Table A2. Transition to *Inactive* (A to I) and to *Active and Accelerate* (A to AAc): linear mixed-effects models for empirical adaptation effects in driver behaviour.

		A to I				A to AAc			
Speed	*Fixed Effects*	*df*	*Error*	*F*	*p-value*	*df*	*Error*	*F*	*p-value*
	Intercept	1	16.46	1850.59	< 0.0005	1	18.69	1366.14	< 0.0005
	Time	19	1936.72	56.30	< 0.0005	19	3247.93	12.93	< 0.0005
	Density	2	110.89	133.23	< 0.0005	2	177.32	168.39	< 0.0005
	System state	2	2149.46	1.43	0.239	2	2664.88	10.41	< 0.0005
	Time*System state	31	1599.19	1.22	0.187	38	1811.64	4.17	< 0.0005
	Time*System state*Density	85	1500.17	1.03	0.415	112	2078.50	1.46	0.001
	Covariance parameters			*Wald Z*	*p-value*			*Wald Z*	*p-value*
	Gamma (var. between driv.)			0.01	0.496			1.57	0.059
	Sigma (var. between obs.)			7.33	< 0.0005			10.18	< 0.0005
	Rho (autoregressive)			1151.35	< 0.0005			1959.96	< 0.0005
	Phi (moving-average)			2301.07	< 0.0005			3923.10	< 0.0005
Acceleration	*Fixed Effects*	*df*	*Error*	*F*	*p-value*	*df*	*Error*	*F*	*p-value*
	Intercept	1	740.21	13.55	< 0.0005	1	20.74	5.95	0.024
	Time	19	1547.78	8.29	< 0.0005	19	2324.19	4.09	< 0.0005
	Density	2	563.93	4.44	0.012	2	205.58	1.53	0.220
	System state	2	1968.06	8.93	< 0.0005	2	3531.06	147.93	< 0.0005
	Time*System state	31	1507.33	0.91	0.604	38	2409.02	2.63	< 0.0005
	Time*System state*Density	85	1379.54	0.94	0.643	112	2535.20	2.43	< 0.0005
	Covariance parameters			*Wald Z*	*p-value*			*Wald Z*	*p-value*
	Gamma (var. between driv.)			–	–			0.82	0.206
	Sigma (var. between obs.)			20.41	< 0.0005			22.87	< 0.0005
	Rho (autoregressive)			34.21	< 0.0005			60.40	< 0.0005
	Phi (moving-average)			79.09	< 0.0005			126.14	< 0.0005

(*continued*).

Table A2. Continued

		A to I				A to AAc			
Ln(Distance headway)	*Fixed Effects*	*df*	*Error*	*F*	*p-value*	*df*	*Error*	*F*	*p-value*
	Intercept	1	26.78	3190.59	< 0.0005	1	13.48	4528.70	< 0.0005
	Time	19	1356.99	5.29	< 0.0005	19	2109.85	4.01	< 0.0005
	Density	2	154.82	37.55	< 0.0005	2	192.94	72.88	< 0.0005
	System state	2	1594.31	1.73	0.177	2	2974.21	11.77	< 0.0005
	Time*System state	31	1337.59	1.03	0.425	38	2165.10	1.91	0.001
	Time*System state*Density	84	1242.33	1.24	0.077	112	2185.09	1.26	0.039
	Covariance parameters			*Wald Z*	*p-value*			*Wald Z*	*p-value*
	Gamma (var. between driv.)			1.59	0.056			1.32	0.093
	Sigma (var. between obs.)			10.37	< 0.0005			12.75	< 0.0005
	Rho (autoregressive)			108.85	< 0.0005			203.86	< 0.0005
	Phi (moving-average)			176.71	< 0.0005			345.89	< 0.0005
Relative speed	*Fixed Effects*	*df*	*Error*	*F*	*p-value*	*df*	*Error*	*F*	*p-value*
	Intercept	1	25.31	14.71	0.001	1	19.36	7.14	0.015
	Time	19	1373.78	5.04	< 0.0005	19	2057.97	2.69	< 0.0005
	Density	2	153.01	3.23	0.042	2	233.74	5.13	0.007
	System state	2	1658.32	0.08	0.924	2	3006.63	8.04	< 0.0005
	Time*System state	31	1323.34	0.61	0.955	38	2149.53	1.43	0.044
	Time*System state*Density	84	1208.22	0.82	0.879	112	2171.00	1.97	< 0.0005
	Covariance parameters			*Wald Z*	*p-value*			*Wald Z*	*p-value*
	Gamma (var. between driv.)			0.20	0.420			2.02	0.022
	Sigma (var. between obs.)			11.16	< 0.0005			14.66	< 0.0005
	Rho (autoregressive)			87.84	< 0.0005			116.97	< 0.0005
	Phi (moving-average)			158.99	< 0.0005			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.