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RESUMING MANUAL CONTROL OR NOT? MODELLING CHOICES OF CONTROL TRANSITIONS IN FULL-RANGE ADAPTIVE CRUISE CONTROL

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ABSTRACT

Automated vehicles and driving assistance systems such as Adaptive Cruise Control (ACC) are expected to reduce traffic congestion, accidents and levels of emissions. Field Operational Tests 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 mathematical models evaluating the impact of ACC do not adequately represent this process.

This research aims to identify the main factors influencing drivers' choice to resume manual control. A mixed logit model that predicts the choice to deactivate the system or overrule it by pressing the gas pedal was estimated. The dataset was collected in an on-road experiment in which twenty-three participants drove a research vehicle equipped with full-range ACC on a 35.5-km freeway in Munich during peak hours.

The results reveal that drivers are 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 are 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 decelerates. Everything else being equal, some drivers have higher probabilities to resume manual control. We conclude that a novel conceptual framework linking ACC system settings, driver behavior characteristics, driver characteristics and environmental factors is needed to model driver behavior in control transitions between ACC and manual driving.

Keywords: Control transitions, Adaptive Cruise Control, on-road experiment, driver behavior, choice model.

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 (*1*). 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 behavior has been extensively analyzed since the 1990s, primarily in driving simulator experiments. FOTs have shown potential safety benefits of ACC systems which are inactive at low speeds when they are activated: drivers maintain larger time headways (*2*-*5*), follow the leader twice as long as in manual driving (*4*), and prepare lane changes in advance to refrain from interactions with slower vehicles (*2*). A possible explanation for these behavioral adaptations is that, when the ACC is active, drivers do not manually control the vehicle (*1*).

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* (*6*) and may have a significant impact on traffic flow efficiency (*7*) and safety. The characteristics of the ACC, the road, traffic flow, and the drivers affect the initiation of these transitions (*8*). Field Operational Tests have shown that dense traffic conditions (*4; 9*) and maneuvers 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 (*10*). 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 (*11; 12*) 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 research explores the factors which 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. The paper is structured as follows. The next section discusses potential reasons for control transitions and limitations of existing models for these transitions. This section is followed by a description of the controlled on-road experiment. Next, the model specification and the estimation results are presented. The last section discusses the main factors influencing transitions to manual control and directions for future research.

LITERATURE REVIEW

In this section, we review available behavioral 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 (*13*)). 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 (*7*)).

Control transitions can be initiated by the driver voluntarily or by the automated system because of its own functioning limitations. Lu and De Winter (*6*) 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 Initiated Driver in Control (DIDC) when drivers deactivate the system, Driver Initiated Automation in Control (DIAC) when drivers activate it, and Automation Initiated Driver in Control (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 (*2; 4; 9; 14*) have investigated driving behavior with ACC systems that are inactive at speeds below 30 km/h and have limited decelerations capabilities. DIAC transitions may occur for comfort reasons (*15; 16*) in non-critical and non-dense traffic situations (e.g., after entering the freeway (*2*)). DIDC transitions by braking have been primarily related to safety indicators such as time to collision. Xiong and

Boyle (*14*) 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 (*17*). Viti et al. (*9*) 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 (*15; 16*) 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 field experiment, Pereira et al. (*18*) 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 behavior 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. (*11*) 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 to synchronize the speed with a deceleration equal to -1 m/s^2. Based on this model and empirical findings by (*9; 15; 16*), Klunder et al. (*12*) 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 (*14*) 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. In this paper, we present 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.

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 1(a, b). 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 preset 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.

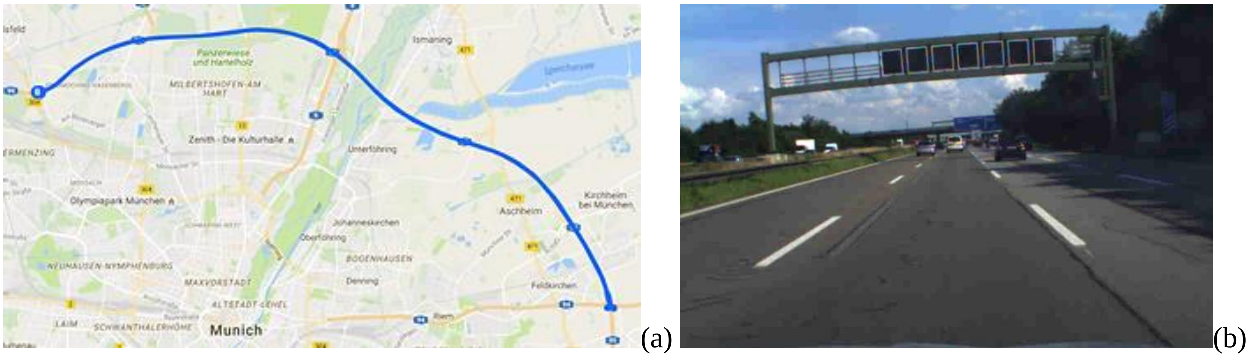

FIGURE 1 Map (*19*) (a) and picture (b) of the test route on the A99 in Munich.

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 desired 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 desired speed as a conventional cruise control system. Figure 2 shows the three states the system can be in (*Inactive*, *Active*, *Active and accelerate*) and the transitions between them.

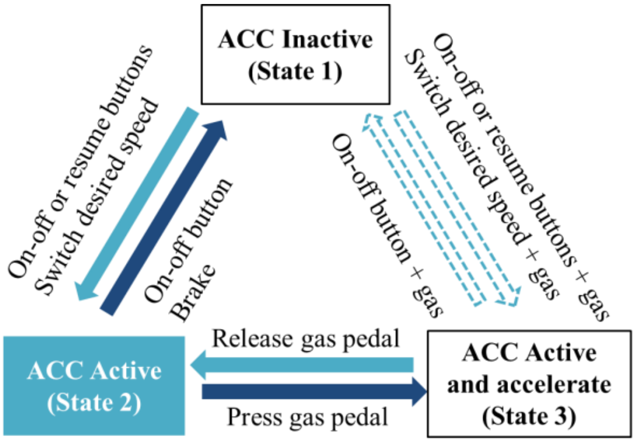

FIGURE 2 ACC system specifications. White boxes represent system states in which drivers are in control and light blue boxes states in which ACC is in control. Solid arrows denote driver initiated control transitions between ACC system states and dashed arrows state transitions. Light blue solid arrows define driver initiated automation in control transitions (DIAC), blue solid arrows driver initiated driver in control transitions (DIDC).

When the system is *Inactive*, it can be activated by pressing the on/off button, the desired 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*.

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 behavior 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).

DATA ANALYSIS

The data collected on the 35.5 km of the experiment for the 23 drivers were analyzed to understand the conditions in which control transitions occurred most often. This paper 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. In this paper, we analyze 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 authority 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 analyzed. Drivers transferred to *Inactive* from 0 to 7 times (M=2.39, SD=1.83), and to *Active and accelerate* from 0 to 30 times (M=7.00, SD=5.88).

In Figure 3, to explore the circumstances in which the control transitions were initiated, we compare the empirical cumulative distribution functions of the driver behavior characteristics when no transitions occurred, when the system was deactivated and when it was overruled. Table 1 presents the mean and the standard deviations of these variables and results of two-sample Kolmogorov-Smirnov tests on the similarity of the distributions among the three groups. Figure 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 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 3(c) shows that 76.1% of the transitions to *Active and accelerate* occurred when the vehicle decelerated. Figure 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 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 3(f) suggests that, on average, deactivations were associated with larger distance headways. Figure 3(g) shows that 80.0% of the deactivations and 65.1 % of the overruling actions occurred when the speed of the subject 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 3(h) indicates that 72.7% 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 maneuvers 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, we assumed that the distance headway reduction was caused by a new vehicle cutting in. We conclude that the driver behavior characteristics of the subject vehicle and the leader may influence significantly the choice to resume manual control.

Freeway sections of increased lane changing, merging and weaving were associated with more frequent control transitions (Table 1). Deactivations occurred more often when drivers were on the freeway mainline close to an on-ramp and in the segment between the first exit sing 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 (*20*).

Significant differences in transferring control were also associated with drivers with different characteristics (Table 1). 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.

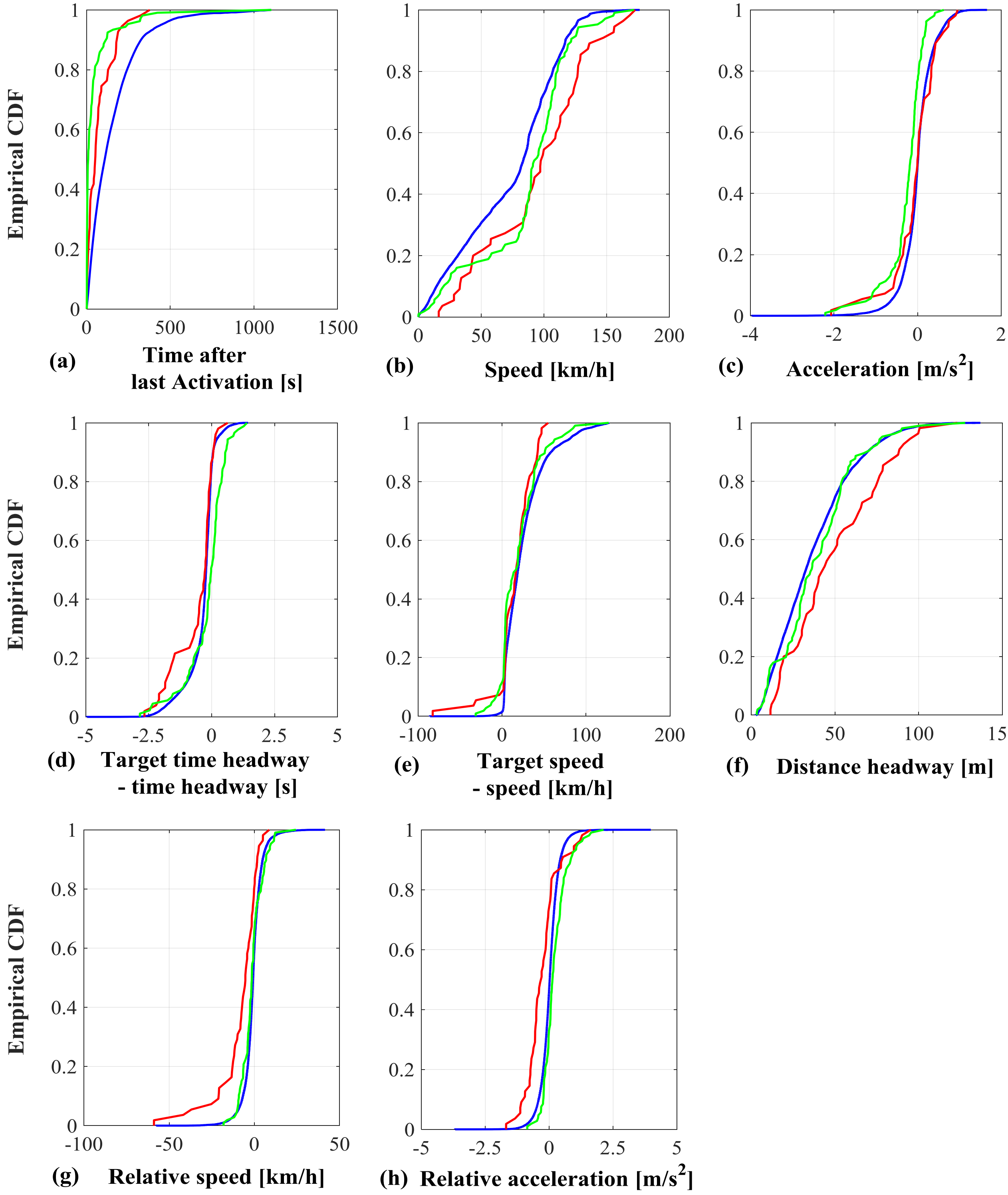

FIGURE 3 Empirical cumulative distribution functions of the driver behavior characteristics when the system is maintained *Active* (blue), and when transitions to *Inactive* (red) and to *Active and accelerate* (green) are initiated. The variables plotted are listed as follows: (a) time after last activation, (b) speed, (c) acceleration, (d) target time headway – time headway, (e) target speed – speed, (f) distance headway, (g) relative speed, and (h) relative acceleration.

TABLE 1 Statistics on the driver behavior characteristics, road sections, and driver characteristics when the system is maintained *Active* (A) and when control transitions are initiated to *Inactive* (I) and to *Active and accelerate* (AAc); (*) p-value>0.05

Driver behavior characteristics

		Mean and standard deviation			*Two-sample Kolmogorov-Smirnov test: p-value*		
Variables	*Description*	*A*	*I*	*AAc*	*A vs. I*	*A vs. AAc*	*I vs. AAc*
Time after last activation	Time after the ACC has been activated in s	152 (155)	76.0 (83.2)	50.3 (128)	$4.73\cdot10^{-5}$	$9.04\cdot10^{-27}$	$8.64\cdot10^{-5}$
Speed	Speed of the subject vehicle in km/h	72.8 (37.9)	94.8 (40.9)	86.5 (36.9)	0.00112	$4.91\cdot10^{-5}$	0.0486
Acceleration	Acceleration of the subject vehicle in m/s^2	-0.00254 (0.390)	-0.0491 (0.549)	-0.272 (0.462)	0.432 (*)	$2.01\cdot10^{-10}$	0.00320
Target time headway – time headway	Difference between the target time headway set in the ACC and the time headway (front bumper to rear bumper) in s	-0.364 (0.561)	-0.574 (0.758)	-0.160 (0.780)	0.192 (*)	$1.79\cdot10^{-11}$	0.000110
Target speed – speed	Difference between the target speed set in the ACC and the subject vehicle speed in km/h	25.6 (25.0)	16.2 (22.2)	20.2 (24.9)	0.239 (*)	0.00655	0.464(*)
Distance headway	Distance headway (front bumper to rear bumper) in m	36.7 (22.9)	49.8 (27.5)	39.1 (23.1)	0.00935	0.147(*)	0.0335
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)	$2.86\cdot10^{-8}$	0.0902(*)	0.000230
Relative acceleration	Difference between the leader acceleration and the subject vehicle acceleration in m/s^2	0.0138 (0.375)	-0.250 (0.645)	0.228 (0.479)	$2.84\cdot10^{-7}$	0.000555	$1.13\cdot10^{-7}$

Road sections

		Observations and percentages per group		
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%)

Driver characteristics

		Observations and percentages per group			*Chi-square test*		
Variables		*A*	*I*	*AAc*	df	χ	p-value
Gender					2	9.49	0.009
	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					2	14.4	0.0007
	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					4	14.9	0.005
	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%)			

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, we 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 (*21*). The choices are modelled for this time interval and are associated with the driver behavior 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, we estimated a mixed logit model introducing a driver-specific error term ϑ_n assumed to be normally distributed over the sample (*21*). 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). Below, we present the final specification, selected based on statistical significance. 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 (1-3):

$$U_n^A(t) = 0 + \varepsilon_n^A(t) \tag{1}$$

$$\begin{aligned} U_n^I(t) = {} & \alpha^{I} + \beta^I_{TimeAct} \cdot \log\big(TimeAct(t)\big) + \beta_{Speed} \cdot Speed(t) \\ & + \beta_{LowTarSpeed} \cdot LowTarSpeed(t) + \beta^I_{THW30} \cdot THW30(t) + \beta^I_{RelSpeed} \cdot RelSpeed(t) \\ & + \beta^I_{RelAcc} \cdot RelAcc(t) + \beta^I_{AntCutIn3} \cdot AntCutIn3(t) + \beta_{OnRamp} \cdot OnRamp(t) \\ & + \beta^I_{Exit} \cdot Exit(t) + \gamma_n \cdot \vartheta_n + \varepsilon^I_n(t) \end{aligned} \tag{2}$$

$$\begin{aligned} U_n^{AAc}(t) = {} & \alpha^{AAc} + \beta^{AAc}_{TimeAct} \cdot \log(TimeAct(t)) + \beta_{Speed} \cdot Speed(t) \\ & + \beta_{LowTarSpeed} \cdot LowTarSpeed(t) + \beta^{AAc}_{Acc-} \cdot AccNeg(t) + \beta^{AAc}_{Acc+} \cdot AccPos(t) \\ & + \beta^{AAc}_{RelSpeed} \cdot RelSpeed(t) + \beta^{AAc}_{CutIn} \cdot CutIn(t) + \beta_{OnRamp} \cdot OnRamp(t) \\ & + \beta^{AAc}_{Female} \cdot Female_n + \beta^{AAc}_{ExpDriv} \cdot ExpDriving_n + \gamma_n \cdot \vartheta_n + \varepsilon^{AAc}_n(t) \end{aligned} \tag{3}$$

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 2, γ_n 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 'mlogit' package (*22*) in R. The log likelihood values, the goodness of fit indicators and the estimation results are presented in Table 2. 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 3(a) and resulted in a significant better fit than a linear specification. This effect is stronger for overruling than for deactivating the system. Analyzing the driver behavior characteristics of the subject vehicle, we note 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 behavior 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 behavior) and to overrule after a vehicle has cut in (reactive behavior). We selected this specification 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 (*18*). 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.

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. We assumed that the driver specific error terms for overruling and deactivating the ACC are equal because these terms were strongly correlated (r = 0.905), 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, we calculated the choice probability ratio 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, we assumed that the ACC system had been activated for 59 s and the observation was not influenced by ramps, exits or cut-in maneuvers. These values were chosen based on the average conditions of the observed control transitions. The results are shown in Figure 4 (ratio variables) and Table 3 (ordinal and nominal variables). All results are consistent with previous discussions. Comparing the plots in Figure 4, we observe 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 3, we note that the probability of deactivations is strongly influenced by the number of vehicles which are expected to cut in in the next three seconds.

TABLE 2 Statistics and estimation results of the mixed logit model; (*) 0.05 <p-value <0.10

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 $\mathcal{L}(c)$	-1067
Final log likelihood $\mathcal{L}(\hat{\beta})$	-816
Adjusted likelihood ratio index (rho-bar-squared) $\bar{\rho}^2 = 1 - \frac{(\mathcal{L}(\hat{\beta}) - \mathrm{K})}{\mathcal{L}(c)}$	0.219

Variable	*Description*	*Parameters*	*Estimate*	*T-test*	
-	Alternative specific constant	α^{I}	-6.52	-11.5	
-	Alternative specific constant	α^{AAc}	-3.01	-7.29	
TimeAct	Time after the ACC has been activated in s	$\beta^{I}_{TimeAct}$	-0.197	-1.79	*
TimeAct	Time after the ACC has been activated in s	$\beta^{AAc}_{TimeAct}$	-0.742	-11.7	
Speed	Speed of the subject vehicle in km/h	β_{Speed}	0.00710	2.83	
LowTarSpeed	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	$\beta_{TarSpeed-}$	-0.0272	-2.00	
AccNeg	Acceleration of the subject vehicle in m/s^2 when this value is negative	β^{AAc}_{Acc-}	-1.52	-5.62	
AccPos	Acceleration of the subject vehicle in m/s^2 when this value is positive	β^{AAc}_{Acc+}	-3.79	-3.33	
THW30	Time headway (front bumper to rear bumper) in s when the speed is higher than 30 km/h	β^{I}_{THW30}	-0.375	-2.06	
RelSpeed	Relative speed (i.e., leader speed – subject vehicle speed) in km/h	$\beta^{I}_{RelSpeed}$	-0.109	-7.19	
RelSpeed	Relative speed (i.e., leader speed – subject vehicle speed) in km/h	$\beta^{AAc}_{RelSpeed}$	0.0560	3.26	
RelAcc	Relative acceleration (i.e., leader acceleration – subject vehicle acceleration) in m/s^2	β^{I}_{RelAcc}	-1.31	-5.33	
AntCutIn3	Number of vehicles that will cut in in the following three seconds	$\beta^{I}_{AntCutIn3}$	1.77	6.60	
CutIn	Dummy variable equal to 1 when a vehicle cuts in in front of the subject	β^{AAc}_{CutIn}	1.05	1.94	*
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 (*20*)	β_{OnRamp}	0.573	3.00	
Exit	Dummy variable equal to 1 when the distance to the closest exit is shorter than 1600 m (first exit sing)	β^{I}_{Exit}	1.90	4.84	
Female	Dummy variable denoting female drivers	β^{AAc}_{Female}	-1.03	-3.61	
ExpDriving	Years of driving experience	$\beta^{AAc}_{ExpDriv}$	-0.0460	-2.84	
ϑ_n	Individual specific error term	γ_n	0.869	6.68	

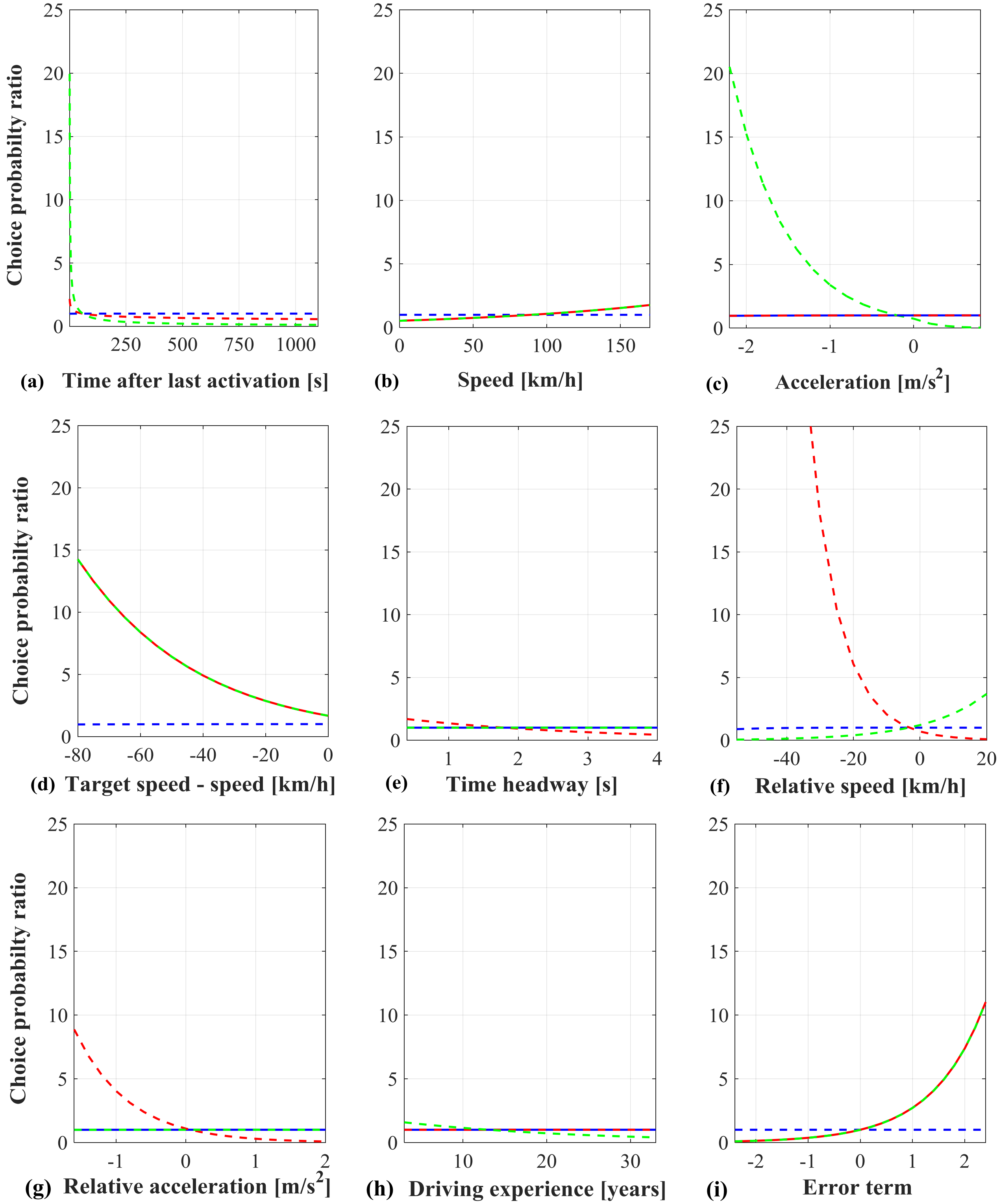

FIGURE 4 Effect of the explanatory variables and driver specific error term on choice probability ratio (probability predicted divided by probability baseline observation) of keeping ACC active (blue), transferring to *Inactive* (red), transferring to *Active and accelerate* (green). The variables plotted are listed as follows: (a) time after last activation, (b) speed, (c) acceleration, (d) target speed – speed, (e) time headway, (f) distance headway, (g) relative speed, (h) relative acceleration, and (i) driver specific error term γ_n .

TABLE 3 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	0.9969	0.9969	2.840
$\text{AntCutIn}_3 = 1$	0.9976	5.873	0.9976
$\text{AntCutIn}_3 = 2$	0.9834	34.08	0.9834
$\text{AntCutIn}_3 = 3$	0.9075	185.1	0.9075
OnRamp	0.9983	1.771	1.771
Exit	0.9971	6.674	0.9971
Female	1.001	1.001	0.3588

DISCUSSION AND CONCLUSIONS

The aim of this paper was to identify 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 (*7*) and safety. To gain empirical insight into the decision-making process, we estimated a mixed logit model with panel data collected in an on-road study. In this model, we found that drivers are more likely to deactivate the system when approaching a slower leader, when driving above the ACC target speed, when expecting vehicles cutting in the following 3 s, and before exiting the freeway. 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.

We conclude 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 (*14; 18*)). 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 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 behavior 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, we need a conceptual framework that links ACC system settings, driver behavior 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.

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