

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

Varotto, Silvia; Farah, Haneen; Toledo, Tomer; van Arem, Bart; Hoogendoorn, Serge

DOI

[10.1016/j.trb.2018.09.007](https://doi.org/10.1016/j.trb.2018.09.007)

Publication date

2018

Document Version

Final published version

Published in

Transportation Research. Part B: Methodological

Citation (APA)

Varotto, S., Farah, H., Toledo, T., van Arem, B., & Hoogendoorn, S. (2018). Modelling decisions of control transitions and target speed regulations in full-range Adaptive Cruise Control based on Risk Allostasis Theory. *Transportation Research. Part B: Methodological*, 117(Part A), 318–341. <https://doi.org/10.1016/j.trb.2018.09.007>

Important note

To cite this publication, please use the final published version (if applicable). Please check the document version above.

Copyright

Other than for strictly personal use, it is not permitted to download, forward or distribute the text or part of it, without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license such as Creative Commons.

Takedown policy

Please contact us and provide details if you believe this document breaches copyrights. We will remove access to the work immediately and investigate your claim.

Green Open Access added to TU Delft Institutional Repository

'You share, we take care!' – Taverne project

<https://www.openaccess.nl/en/you-share-we-take-care>

Otherwise as indicated in the copyright section: the publisher is the copyright holder of this work and the author uses the Dutch legislation to make this work public.



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

Silvia F. Varotto^{a,*}, Haneen Farah^a, Tomer Toledo^b, Bart van Arem^a,
Serge P. Hoogendoorn^a

^a Department of Transport and Planning, Faculty of Civil Engineering and Geosciences, Delft University of Technology, Stevinweg 1, P.O. Box 5048, Delft 2600 GA, The Netherlands

^b Transportation Research Institute, Faculty of Civil and Environmental Engineering, Technion - Israel Institute of Technology, 711 Rabin Building, Haifa 32000, Israel

ARTICLE INFO

Article history:

Received 30 April 2018

Revised 5 August 2018

Accepted 7 September 2018

Available online 19 September 2018

Keywords:

Control transitions

Adaptive Cruise Control

On-road experiment

Driver behaviour

Continuous-discrete choice model

ABSTRACT

Adaptive Cruise Control (ACC) and automated vehicles can contribute to reduce traffic congestion and accidents. Recently, an on-road study has shown that drivers may prefer to deactivate full-range ACC when closing in on a slower leader and to overrule it by pressing the gas pedal a few seconds after the activation of the system. Notwithstanding the influence of these control transitions on driver behaviour, a theoretical framework explaining driver decisions to transfer control and to regulate the target speed in full-range ACC is currently missing.

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

The model was estimated using a dataset collected in an on-road experiment with full-range ACC. The results reveal that driver decisions to resume manual control and to regulate the target speed in full-range ACC can be interpreted based on the RAT. The model can be used to forecast driver response to a driving assistance system that adapts its settings to prevent control transitions while guaranteeing safety and comfort. The model can also be implemented into a microscopic traffic flow simulation to evaluate the impact of ACC on traffic flow efficiency and safety accounting for control transitions and target speed regulations.

© 2018 Elsevier Ltd. All rights reserved.

1. Introduction

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

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

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

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

This study develops such a mathematical framework to model driver decisions to resume manual control and to regulate the target speed in full-range ACC. The model is based on the Risk Allostasis Theory (RAT) (Fuller, 2011), captures explicitly interdependencies between the two decisions, and can be fully estimated based on driver behaviour data. The paper is organised as follows. Section 2 reviews driver control theories and driver behaviour models that are suitable to explain driver interaction with ACC. This section concludes with the identified research gaps. Section 3 proposes the con-

* Corresponding author.

E-mail addresses: s.f.varotto@tudelft.nl (S.F. Varotto), h.farah@tudelft.nl (H. Farah), toledo@technion.ac.il (T. Toledo), b.vanarem@tudelft.nl (B. van Arem), s.p.hoogendoorn@tudelft.nl (S.P. Hoogendoorn).

ceptual model framework for driver decisions to resume manual control and to regulate the target speed in full-range ACC. Section 4 describes the mathematical formulation of the modelling framework and Section 5 the maximum likelihood estimation method. Section 6 presents the case study, including a description of the on-road experiment, the data analysis, the estimation results, and validation analyses of the model. Section 7 summarizes the main contributions of the proposed modelling framework and directions for future research.

2. Literature review

The literature review focuses on studies proposing conceptual and mathematical models of driver behaviour that are suitable to explain control transitions and target speed regulation in ACC. Section 2.1 introduces driver control theories and Section 2.2 conceptual models explaining adaptations in driver behaviour. Section 2.3 discusses a model framework that has the potential to capture interdependencies between different driver behaviours. Section 2.4 summarizes the research gaps and formulates the research objectives.

2.1. Driver control theories

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

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

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

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

2.2. Conceptual models for adaptations in driver behaviour

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

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

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

2.3. Integrated driver behaviour models

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

2.4. Research gaps and objectives

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

- (1) to develop a conceptual model framework that explains driver decisions to resume manual control and to regulate the target speed grounded on the Risk Allostasis Theory (Fuller, 2011);
- (2) to develop a mathematical formulation for this modelling framework based on the integrated driver behaviour models (Toledo, 2003), which describes underlying constructs, captures interdependencies between different decisions, and can be fully estimated using driver behaviour data.

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

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

Fig. 1 presents the model framework. We propose two levels of decision making describing both transitions to manual control (discrete choice) and target speed regulations (continuous choice) with ACC: risk feeling and task difficulty evaluation, and ACC system state and ACC target speed regulation choice. The decision-making process is latent (unobservable). Driver actions to resume manual control and to regulate the target speed are observed, while the perceived level of RFTD is latent. At the highest level, the driver evaluates whether the perceived level of RFTD falls within the *range* which is considered *acceptable* to maintain the ACC active and the current ACC target speed. The perceived RFTD is influenced by the driver behaviour characteristics of the subject vehicle and of the leader. The acceptable range with the ACC active varies between drivers and within drivers over time, being influenced by driver characteristics, by the functioning of the system, and by the environment. If the perceived RFTD level is higher than the maximum value acceptable, the driver will choose to deactivate the system or to decrease the ACC target speed maintaining the system active. If the perceived RFTD level is lower than the minimum value acceptable, the driver will choose to overrule the ACC by pressing the gas pedal, to increase the ACC target speed maintaining the system active, or not to intervene. The latter is introduced to capture drivers' difficulties to perceive changes in feeling of risk and task difficulty in low risk situations, which might be influenced by human factors (unobservable) such as errors, shifts in attention and distraction (Fuller and Santos, 2002). These decisions are influenced by the driver behaviour characteristics, by the functioning of the system, by environmental conditions, and by driver characteristics.

The model framework allows capturing directly drivers' propensity to maintain the ACC system active and interdependencies among decisions to transfer control and to regulate the target speed through appropriate model specifications at the different levels of decision making. This is further explained in Section 4, which presents the mathematical formulation of the model based on this conceptual structure.

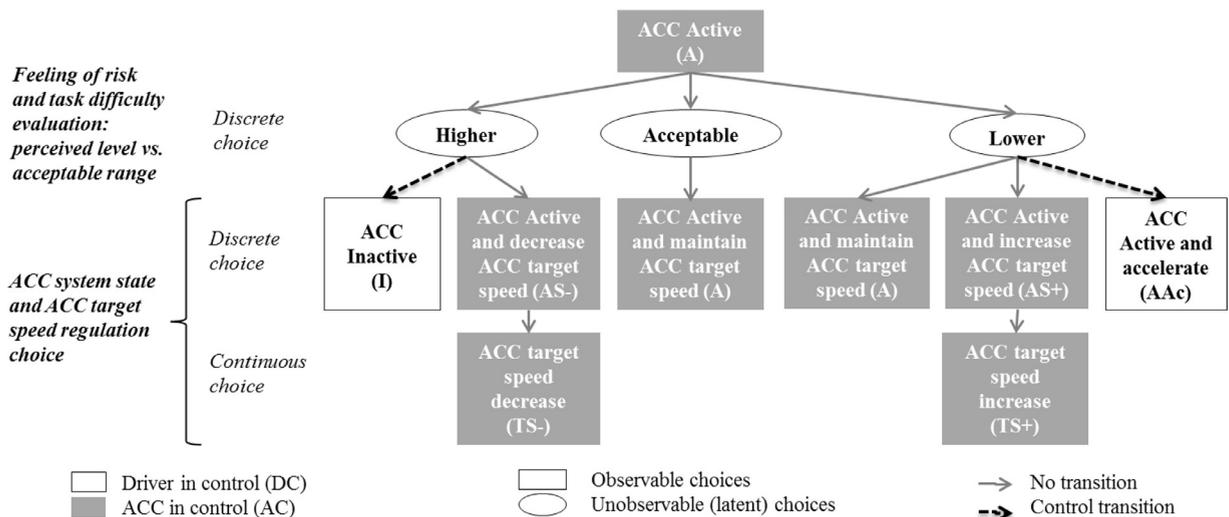


Fig. 1. Conceptual model for driver decisions to resume manual control and to regulate the target speed in full-range ACC.

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

To implement the conceptual model presented in Section 3, we need a flexible mathematical framework which is able to capture unobservable constructs and interdependencies between different decisions made by the same driver. Modelling frameworks based on choice models satisfy these requirements. In this study, choice models are preferred to alternative methods (e.g., artificial intelligence) because the model structure can be selected based on insights from driver control theories and the estimation results are directly interpretable.

In this mathematical framework, the magnitude of the ACC target speed regulation is chosen simultaneously to the system state and correlations between these two choices are captured explicitly. In addition, interdependencies across decisions are addressed in terms of causality, unobserved driver characteristics, and state dependency (Toledo, 2003). Causality is addressed by modelling the decisions taken at the lower levels as conditional on the decisions taken at the higher levels. This two-level model structure allows capturing explicitly drivers' propensity to not intervene when the ACC system is active. Unobserved driver characteristics are modelled by introducing driver-specific error terms in each level of decision making. State dependency (i.e., interdependencies between choice situations over time) is addressed by including the driver behaviour characteristics of the subject vehicle and of its direct leader as explanatory variables in the different levels. The model formulation is presented in Sections 4.1–4.3.

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

The risk feeling and task difficulty evaluation (RFTDE) model is formulated as a generalized ordered probit model with random thresholds (Castro et al., 2013; Eluru et al., 2008; Greene and Hensher, 2009, 2010). This model formulation represents the ordinal and discrete nature of the risk feeling and task difficulty evaluation (risk lower than acceptable, acceptable risk, and risk higher than acceptable), capturing both observed and unobserved heterogeneity in the minimum and in the maximum risk acceptable. This ordinal response structure is based on the assumption that an unobservable risk feeling and task difficulty (RFTD) determines the observable decisions of drivers. The RFTD is modelled as a latent variable that follows a normal distribution. Driver n chooses at time t whether the perceived RFTD is lower than the minimum risk acceptable (L), falls within the acceptable risk range (Ac) or is higher than the maximum risk acceptable (H) as presented in Eq. (1):

$$RFTDE_n(t) = \begin{cases} L, & RFTD_n(t) < MinAc_n(t) \\ Ac, & MinAc_n(t) < RFTD_n(t) < MaxAc_n(t) \\ H, & RFTD_n(t) > MaxAc_n(t) \end{cases} \quad (1)$$

where RFTDE is the choice indicator, and $MinAc_n(t)$ and $MaxAc_n(t)$ are the variables that represent the minimum and the maximum acceptable risk for each driver at time t . The non-linear formulation of the minimum and of the maximum risk acceptable allows to distinguish mathematically the thresholds from the latent regression, guarantees that both thresholds are positive, and preserves the ordering of the thresholds ($-\infty < MinAc_n(t) < MaxAc_n(t) < \infty$) (Greene and Hensher, 2009, 2010). The lowest and the highest acceptable risk are functions of explanatory variables as shown in Eqs. (2)–(3):

$$MinAc_n(t) = \exp(\mu^L + \boldsymbol{\tau}^L \cdot \mathbf{X}_n^L(\mathbf{t}) + \gamma^L \cdot \vartheta_n) \quad (2)$$

$$MaxAc_n(t) = MinAc_n(t) + \exp(\mu^H + \boldsymbol{\tau}^H \cdot \mathbf{X}_n^H(\mathbf{t}) + \gamma^H \cdot \vartheta_n) \quad (3)$$

where μ^L and μ^H are the constants, $\boldsymbol{\tau}^L$ and $\boldsymbol{\tau}^H$ are vectors of parameters associated with the explanatory variables $\mathbf{X}_n^L(\mathbf{t})$ and $\mathbf{X}_n^H(\mathbf{t})$, γ^L and γ^H are the parameters associated with the individual-specific error term $\vartheta_n \sim N(0, 1)$. The thresholds vary within individuals over time due to observed variables and between individuals due to observed variables and unobserved heterogeneity. Relevant explanatory variables that can be included into the threshold equations are driver characteristics, variables related to the functioning of the ACC system, and characteristics of the freeway segment. The driver-specific error term ϑ_n captures unobserved preferences that influence all choices taken by the individual over time. This error term varies between drivers but it is constant between choice situations for the same driver. The mean risk feeling and task difficulty perceived by drivers is a function of explanatory variables as described in Eq. (4):

$$RFTD_n(t) = \omega + \boldsymbol{\lambda} \cdot \mathbf{X}_n(\mathbf{t}) + \sigma \cdot \delta_n(t) \quad (4)$$

where ω is the constant, $\boldsymbol{\lambda}$ is a vector of parameters associated with the explanatory variables $\mathbf{X}_n(\mathbf{t})$, and σ is the parameter associated with the observation-specific error term $\delta_n(t) \sim N(0, 1)$. Relevant explanatory variables are the driver behaviour characteristics of the subject vehicle and of the leader, such as speed, relative speed, and distance headway (Fuller, 2011). The observation-specific error term captures unexplained variability between choice situations. The risk feeling and task difficulty evaluation conditional on the value of ϑ_n is calculated as follows in Eqs. (5)–(7):

$$P(RFTDE_n(t) = L|\vartheta_n) = \Phi\left(\frac{MinAc_n(t) - \omega - \lambda \cdot X_n(t)}{\sigma}\right) \tag{5}$$

$$P(RFTDE_n(t) = Ac|\vartheta_n) = \Phi\left(\frac{MaxAc_n(t) - \omega - \lambda \cdot X_n(t)}{\sigma}\right) - \Phi\left(\frac{MinAc_n(t) - \omega - \lambda \cdot X_n(t)}{\sigma}\right) \tag{6}$$

$$P(RFTDE_n(t) = H|\vartheta_n) = 1 - \Phi\left(\frac{MaxAc_n(t) - \omega - \lambda \cdot X_n(t)}{\sigma}\right) \tag{7}$$

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

4.2. Level 2: choice of ACC system state (discrete choice)

Drivers who consider the RFTD lower than the minimum value acceptable choose to overrule the ACC by pressing the gas pedal (AAc), to maintain the system active and increase the target speed (AS+), or not to intervene (AL). This decision is formulated as a logit model, in which the utility functions U for driver n at time t are given by Eqs. (8)–(10):

$$U_n^{AAc}(t) = \alpha^{AAc} + \beta^{AAc} \cdot X_n^{AAc}(t) + \gamma^{AAc} \cdot \vartheta_n + \varepsilon_n^{AAc}(t) \tag{8}$$

$$U_n^{AS+}(t) = \beta^{AS+} \cdot X_n^{AS+}(t) + \varepsilon_n^{AS+}(t) \tag{9}$$

$$U_n^{AL}(t) = \alpha^{AL} + \gamma^{AL} \cdot \vartheta_n + \varepsilon_n^{AL}(t) \tag{10}$$

where α^{AAc} and α^{AL} are alternative specific constants, β^{AAc} and β^{AS+} are vectors of parameters associated with the explanatory variables $X_n^{AAc}(t)$ and $X_n^{AS+}(t)$, γ^{AAc} and γ^{AL} are the parameters associated with the individual-specific error term $\vartheta_n \sim N(0, 1)$, and $\varepsilon_n^{AAc}(t)$, $\varepsilon_n^{AS+}(t)$, and $\varepsilon_n^{AL}(t)$ are i.i.d. Gumbel – distributed error terms. In the utility of not intervening in low risk conditions, the constant and the driver-specific error term are estimated while the explanatory variables are assumed to have an impact equal to zero for identification purposes (Choudhury, 2007; Choudhury et al., 2007). Relevant explanatory variables can include the driver behaviour characteristics of the subject vehicle and of its leader, variables related to the functioning of the system, characteristics of the freeway segment, and driver characteristics. The probability of choosing the ACC system state $k \in C_l$ with $C_l = \{AAc, AS+, AL\}$ in low risk situations is presented in Eq. (11):

$$P(Y_n(t) = k|RFTDE_n(t) = L, \vartheta_n) = \frac{\exp(\alpha^k + \beta^k \cdot X_n^k(t) + \gamma^k \cdot \vartheta_n)}{\sum_l \exp(\alpha^l + \beta^l \cdot X_n^l(t) + \gamma^l \cdot \vartheta_n)} \tag{11}$$

Drivers who consider the RFTD higher than the maximum value acceptable choose to deactivate the ACC (I) or to maintain the system active and decrease the target speed ($AS-$). This decision is formulated as a logit model, in which the utility functions U for driver n at time t are given by Eqs. (12)–(13):

$$U_n^I(t) = \alpha^I + \beta^I \cdot X_n^I(t) + \gamma^I \cdot \vartheta_n + \varepsilon_n^I(t) \tag{12}$$

$$U_n^{AS-}(t) = 0 + \varepsilon_n^{AS-}(t) \tag{13}$$

where α^I is an alternative specific constant, β^I is the vector of parameters associated with the explanatory variables $X_n^I(t)$, γ^I is the parameters associated with the individual-specific error term $\vartheta_n \sim N(0, 1)$, and $\varepsilon_n^I(t)$, and $\varepsilon_n^{AS-}(t)$ are i.i.d. Gumbel – distributed error terms. Relevant explanatory variables are similar to those listed above for low risk conditions. The probability of choosing the ACC system state $i \in C_h$ with $C_h = \{I, AS-\}$ in high risk situations is presented in Eq. (14):

$$P(Y_n(t) = i|RFTDE_n(t) = H, \vartheta_n) = \frac{\exp(\alpha^i + \beta^i \cdot X_n^i(t) + \gamma^i \cdot \vartheta_n)}{\sum_h \exp(\alpha^h + \beta^h \cdot X_n^h(t) + \gamma^h \cdot \vartheta_n)} \tag{14}$$

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

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

ACC target speed regulations are observed only when drivers choose to regulate the ACC target speed. The magnitude of the regulation depends on the choice of increasing or decreasing the ACC target speed. In this framework, decisions to increase or decrease the ACC target speed are captured explicitly (i.e., if a driver chooses to increase the ACC target speed, the increase will be always positive). To represent this process, the error term is assumed to be a positive random variable.

In this case study, the absolute values of the observed ACC target speed increase (*ACCTarSpeed+*) and decrease (*ACCTarSpeed-*) are log-transformed. The regression equations of the ACC target speed increase (Y_n^{TS+}) and decrease (Y_n^{TS-}) conditional upon choosing to increase or decrease the ACC target speed are given in Eqs. (15)–(16):

$$Y_n^{TS+}(t) = \eta^{TS+} + \xi^{TS+} \cdot \mathbf{X}_n^{TS+}(t) + \sum_{j \neq AS+} \varphi_j^{TS+} \cdot C_j^{TS+} + \gamma^{TS+} \cdot \vartheta_n + \omega^{TS+} \cdot v_n^{TS+}(t) \tag{15}$$

$$Y_n^{TS-}(t) = \eta^{TS-} + \xi^{TS-} \cdot \mathbf{X}_n^{TS-}(t) + \varphi_l^{TS-} \cdot C_l^{TS-} + \gamma^{TS-} \cdot \vartheta_n + \omega^{TS-} \cdot v_n^{TS-}(t) \tag{16}$$

where $\eta^{TS+(-)}$ is the constant, $\xi^{TS+(-)}$ is the vector of parameters associated with the explanatory variables $\mathbf{X}_n^{TS+(-)}(t)$, φ_j^{TS+} with $j \in \{AAc, AL\}$ and φ_l^{TS-} are the parameters associated with the selectivity correction terms C_j^{TS+} and C_l^{TS-} respectively, $\gamma^{TS+(-)}$ is the parameter associated with the individual-specific error term $\vartheta_n \sim N(0, 1)$, $\omega^{TS+(-)}$ is the parameter associated with the observation-specific error term $v_n^{TS+(-)}(t) \sim N(0, 1)$. Relevant explanatory variables can include the driver behaviour characteristics of the subject vehicle and of its leader, variables related to the functioning of the system, characteristics of the freeway segment, and driver characteristics. The selectivity correction terms C_j^{TS+} and C_l^{TS-} are given in Eqs. (17)–(18):

$$C_j^{TS+} = \left[\frac{P^j \cdot \ln(P^j)}{1 - P^j} + \ln(P^{AS+}) \right] \tag{17}$$

$$C_l^{TS-} = \left[\frac{P^l \cdot \ln(P^l)}{1 - P^l} + \ln(P^{AS-}) \right] \tag{18}$$

where P^{AAc} , P^{AL} and P^{AS+} are the choice probabilities to overrule the ACC system, not to intervene, and to increase the target speed in the low risk logit model (Eq. (11)), and P^l and P^{AS-} are the choice probabilities to deactivate and decrease the target speed in the high risk logit model (Eq. (14)). The inclusion of the selectivity correction terms into the regression equations corrects for the system state selectivity bias under the assumption that the choice probabilities are logit and the error terms are normally distributed (Dubin and McFadden, 1984; Train, 1986). These correction terms capture unobserved factors that influence both the probability of the system state choice and the magnitude of the target speed regulation. The probability density functions of the target speed increase and decrease conditional on the choices to decrease or increase the ACC target speed are given by Eqs. (19)–(20):

$$\begin{aligned} P\{Y_n^{TS+}(t) = \log(|ACCTarSpeed_n^+(t)|) | Y_n(t) = AS+, RFTDE_n(t) = L, \vartheta_n\} \\ = \frac{1}{\omega^{TS+}} \Phi \left(\frac{\log(|ACCTarSpeed_n^+(t)|) - \eta^{TS+} - \xi^{TS+} \cdot \mathbf{X}(t) - \sum_{j \neq AS+} \varphi_j^{TS+} \cdot C_j^{TS+} - \gamma^{TS+} \cdot \vartheta_n}{\omega^{TS+}} \right) \end{aligned} \tag{19}$$

$$\begin{aligned} P\{Y_n^{TS-}(t) = \log(|ACCTarSpeed_n^-(t)|) | Y_n(t) = AS-, RFTDE_n(t) = H, \vartheta_n\} \\ = \frac{1}{\omega^{TS-}} \Phi \left(\frac{\log(|ACCTarSpeed_n^-(t)|) - \eta^{TS-} - \xi^{TS-} \cdot \mathbf{X}(t) - \varphi_l^{TS-} \cdot C_l^{TS-} - \gamma^{TS-} \cdot \vartheta_n}{\omega^{TS-}} \right) \end{aligned} \tag{20}$$

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

5. Maximum likelihood estimation of the integrated continuous-discrete choice model

The parameters of the choice models and of the regression models are estimated simultaneously with full information maximum likelihood methods. Given $Y_n(t)$ the indicator associated with the system state choice, $Y_n^{TS}(t)$ the indicator associated with the observed values of the ACC target speed regulations, and $RFTDE_n(t)$ the indicator associated with the unobservable risk feeling and task difficulty evaluation, the unconditional probability of deactivating (or overruling) the system (Eq. (21)), of increasing (or decreasing) the ACC target speed (Eq. (22)), and of not intervening (Eq. (23)) in a single observation are given as follows:

$$P(Y_n(t) | \vartheta_n) = P(Y_n(t) | RFTDE_n(t), \vartheta_n) \cdot P(RFTDE_n(t) | \vartheta_n) \tag{21}$$

$$P(Y_n(t), Y_n^{TS}(t) | \vartheta_n) = P(Y_n^{TS}(t) | Y_n(t), RFTDE_n(t), \vartheta_n) \cdot P(Y_n(t) | RFTDE_n(t), \vartheta_n) \cdot P(RFTDE_n(t) | \vartheta_n) \tag{22}$$

$$\begin{aligned} P(Y_n(t) | \vartheta_n) = P(RFTDE_n(t) = Ac | \vartheta_n) \\ + P(Y_n(t) = AL | RFTDE_n(t) = L, \vartheta_n) \cdot P(RFTDE_n(t) = L | \vartheta_n) \end{aligned} \tag{23}$$

where $P(Y_n^{TS}(t)|\cdot)$ is presented in Eqs. (19)–(20), $P(Y_n(t)|\cdot)$ in Eqs. (11) and (14), and $P(RFTDE_n(t)|\cdot)$ in Eqs. (5)–(7). Notably, the unconditional probability of not intervening is the sum of the probabilities of perceiving the feeling of risk as to be acceptable and of not intervening when the feeling of risk is lower than the minimum risk acceptable. This formulation allows decisions of not intervening to arise from two different levels of perceived risk (acceptable and low) and captures explicitly drivers' propensity to not intervene when the system is active (Greene et al., 2013). The joint probability of the T observations over time for the same driver is given by Eq. (24):

$$P(Y_n(1), Y_n^{TS}(1), \dots, Y_n(T), Y_n^{TS}(T) | \vartheta_n) = \prod_{t=1}^T P(Y_n(t), Y_n^{TS}(t) | \vartheta_n) \quad (24)$$

The unconditional joint probability of the observations for each driver is obtained by integrating over the distribution of ϑ_n , which is assumed to be standard normal, as presented in Eq. (25):

$$P(Y_n(1), Y_n^{TS}(1), \dots, Y_n(T), Y_n^{TS}(T)) = \int_{-\infty}^{+\infty} P(Y_n(1), Y_n^{TS}(1), \dots, Y_n(T), Y_n^{TS}(T) | \vartheta) \Phi(\vartheta) d\vartheta \quad (25)$$

The integral is calculated using Monte-Carlo integration. The random draws are generated using the 'Modified Latin Hypercube Sampling' method (Hess et al., 2006). The log-likelihood function for all drivers $1, \dots, N$ is given by Eq. (26):

$$LL = \sum_{n=1}^N \ln [P(Y_n(1), Y_n^{TS}(1), \dots, Y_n(T), Y_n^{TS}(T))] \quad (26)$$

6. Case study

The model can be estimated using driving behaviour data with ACC and information on individual drivers. Section 6.1 briefly describes the on-road experiment, the characteristics of the ACC system, and the participants (for a detailed description, see Varotto et al., 2017). Section 6.2 presents the analysis of the data to explore the conditions in which drivers resumed manual control and regulated the target speed. Section 6.3 discusses the estimation results of the model and the impact of the explanatory variables on the choice probabilities. Section 6.4 proposes *in-sample-out-of-time* and *out-of-sample-in-time* validation analyses of the model estimated.

6.1. Data collection

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

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

Twenty-three participants recruited among BMW employees in Munich completed the experiment. Fifteen participants were male, and eight were female. Participants had between 3 and 33 years of driving experience. Six participants had never used ADAS (Advanced Driving Assistance Systems) before the experiment (no experience), nine had driven with ADAS less often than once a month during the previous year (medium experience), and eight once a month or more often (high experience). None of them had been directly working on the development of the ACC system. Before the experiment, participants were instructed on the specifications of the system, signed an informed consent form, and filled a questionnaire reporting demographic characteristics (Kyriakidis et al., 2014), driving experience (Kyriakidis et al., 2014), experience with ADAS, and driving styles (Taubman-Ben-Ari et al., 2004). The experiment was carried out during the peak hours of the morning (7–9 am) and of the evening (4–6 pm, 6–8 pm) from June 29th to July 9th 2015. Participants drove between 45 and 90 min, based on the traffic flow conditions. Speed, acceleration, distance headway (from radar), speed of the leader (from radar), ACC system settings and state, and GPS position were measured and registered in the Controller Area Network (CAN) of the instrumented vehicle. After the experiment, participants filled a questionnaire about the usage of the ACC system, workload experienced (Byers et al., 1989; Kyriakidis et al., 2014), and the usefulness and satisfaction of the system (Kyriakidis et al., 2014; Van der Laan et al., 1997). The empirical cumulative distribution functions of the driver characteristics reported in the questionnaire are presented in Appendix A, Fig. A1. Drivers reported higher scores on the patient and careful driving style than on the other driving styles, which is similar to previous findings (Taubman-Ben-Ari et al., 2004). Drivers reported low to medium levels of workload while driving with ACC and medium to high levels of usefulness and satisfaction with the system.

Table 1

Mean and standard deviation of the driver behaviour characteristics when drivers transfer the ACC to Inactive (I), decrease the ACC target speed (AS-), maintain the ACC Active (A), increase the ACC target speed (AS+), and transfer to Active and accelerate (AAc); a reduced version of this table focusing on transitions to manual control was presented in Varotto et al. (2017).

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

6.2. Data analysis

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

To gain insight into the conditions in which control transitions and speed regulations were initiated, we analysed the empirical distribution functions of the driver behaviour characteristics when neither transitions nor speed regulations happened, when the ACC was deactivated or overruled, and when the ACC target speed was reduced or increased (Appendix A, Fig. A2). The mean and the standard deviation of these variables are presented in Table 1. The similarity of the distributions between the different groups was tested using two-sample Kolmogorov-Smirnov tests (Appendix A, Table A1). Most transitions to *Active and accelerate* were initiated a few seconds after the activation. At high speeds, deactivations and target speed reductions occurred more often than overruling actions and target speed increments. When the vehicle decelerated, transitions to *Active and accelerate* happened more often than target speed increments. Deactivations happened more often than target speed reductions when the target speed was lower than the actual speed. Overruling actions occurred more often than target speed increments when the target speed was higher than the actual speed. On average, deactivations and target speed reductions were associated with larger distance headways. Deactivations and target speed reductions happened most often when the subject vehicle was faster than the leader, while target speed increments happened most often when the subject vehicle was slower. Most deactivations occurred when the subject vehicle accelerated more than the leader. Most target speed regulations ranged between -20 and $+20$ km/h. In addition, cut-in manoeuvres were detected as described in Varotto et al. (2017). These findings suggest that the driver behaviour characteristics of the subject vehicle and of the leader may impact significantly drivers' decisions to regulate the target speed and to resume manual control.

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

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

6.3. Estimation results

In this case study, we assumed that only one decision happens within a 1-s interval. This interval of time is similar to the mean reaction time between the recognition of a stimulus and the execution of the response in literature (Toledo, 2003). The decisions are related to the driver behaviour characteristics recorded at the beginning of the interval. Multiple 1-s observations, repeated over time, are available for each driver (panel data). Notably, the model specification presented in this section is the result of an intensive modelling process in which several specifications and model structures were compared based on statistical tests. We estimated the model using the software PythonBiogeme (Bierlaire, 2016). All model components were estimated simultaneously using full information maximum likelihood methods as described in Section 5. The log likelihood and the goodness of fit indicators are presented in Table 2 and the estimation results in Tables 3–5. Most parameters are statistically significant at the 95% confidence level. Sections 6.3.1–6.3.3 discuss the estimation results of each model component and Section 6.3.4 presents the impact of the explanatory variables on the unconditional ACC system state choice probabilities and on the magnitude of the target speed regulation.

6.3.1. Risk feeling and task difficulty evaluation

In the ordered probit model, the risk feeling and task difficulty RFTD are influenced by the driver behaviour characteristics of the subject vehicle and of its leader as shown in Eq. (27):

$$\begin{aligned} RFTD_n(t) = & \omega + \lambda_{\frac{Speed}{DHW}} \cdot \frac{Speed(t)}{DHW(t)} + \lambda_{RelSpeed} \cdot RelSpeed(t) \\ & + \lambda_{RelAcc} \cdot RelAcc(t) + \lambda_{AntCutIn3} \cdot AntCutIn3(t) + \delta_n(t) \end{aligned} \quad (27)$$

where ω is the constant, $\lambda_{\frac{Speed}{DHW}}$, $\lambda_{RelSpeed}$, λ_{RelAcc} , $\lambda_{AntCutIn3}$ are the parameters associated with the explanatory variables listed in Table 3, and $\delta_n(t) \sim N(0, 1)$ is the observation-specific error term. Speed is divided by distance headway because drivers are assumed to be more sensitive to changes in risk feelings at short distance headways and at high speeds. In addition, speed and distance headway are highly correlated. The lowest and the highest acceptable risk are functions of the functioning of the ACC system and driver characteristics as presented in Eqs. (28)–(29):

$$MinAc_n(t) = \exp(\tau_{TimeAct}^L \cdot \log(TimeAct(t)) + \tau_{PatCar}^L \cdot PatCar_n + \gamma^L \cdot \vartheta_n) \quad (28)$$

$$MaxAc_n(t) = MinAc_n(t) + \exp(\mu^H + \tau_{TimeAct}^H \cdot \log(TimeAct(t)) + \tau_{PatCar}^H \cdot PatCar_n + \gamma^H \cdot \vartheta_n) \quad (29)$$

where μ^H is the constant, $\tau_{TimeAct}^L$, τ_{PatCar}^L , $\tau_{TimeAct}^H$, and τ_{PatCar}^H are the parameters associated with the explanatory variables listed in Table 3, γ^L and γ^H are the parameters associated with the individual-specific error term $\vartheta_n \sim N(0, 1)$. The logarithmic transformation of the time after last activation is consistent with the empirical findings and showed a significant better fit than a linear specification. The road location, the other driving styles (reckless and careless, angry and hostile, and anxious), gender, age, experience with ADAS, workload, and usefulness and satisfaction with ACC did not influence significantly the acceptable range.

The estimation results in Table 3 show that drivers perceive higher risk at higher speeds and at shorter distance headways. In addition, they perceive higher risks when they are faster (negative relative speed) and accelerate more (negative relative acceleration) than the leader, and when they suppose that a vehicle will cut in during the next three seconds. To analyse the impact of variations in the explanatory variables in the threshold equations, we calculated the lowest and highest risk acceptable with ACC active and the mean feeling of risk in observations in which only one explanatory variable was altered while maintaining all the other variables fixed. We assumed that, in the baseline observation, the driver had experience with ADAS and a score on the patient and careful driving style equal to the mean in this sample. The speed was equal

Table 2
Statistics of the continuous-discrete choice model.

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

Table 3
 Estimation results of the continuous-discrete choice model: risk feeling and task difficulty evaluation.

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

Note: ¹Variable centred on the mean value between drivers.

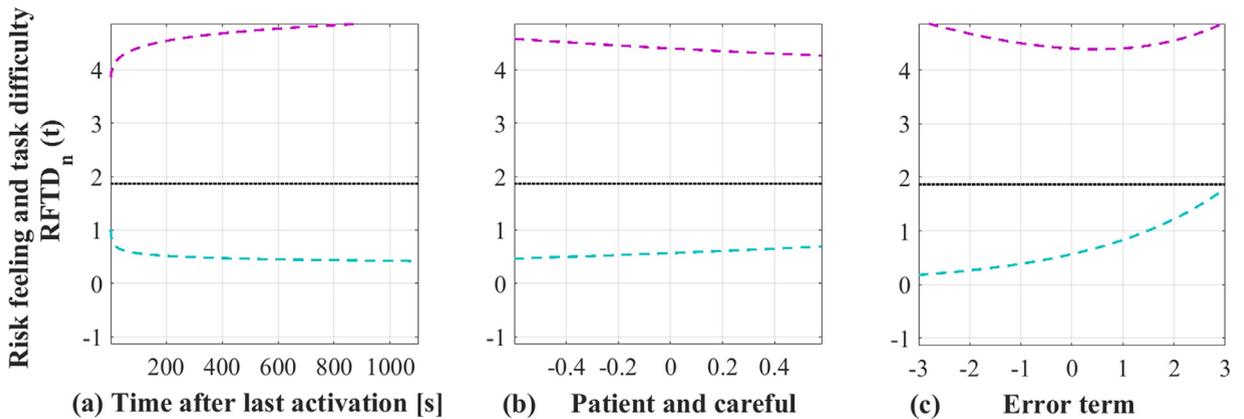


Fig. 2. Impact of the explanatory variables and of the driver-specific error term on the minimum (light blue dashed line) and on the maximum (purple dashed line) risk acceptable with ACC active, compared to the mean feeling of risk and task difficulty (black dotted line). The variables are listed as follows: (a) time after last activation, (b) patient and careful driving style (centred on the mean value between drivers), and (c) driver-specific error term. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

to 87.2 km/h, the ACC target speed 102 km/h, the acceleration -0.0467 m/s^2 , the distance headway 45.3 m, the relative speed -0.781 km/h , and the relative acceleration 0.0365 m/s^2 . The ACC system had been activated for 94 s and cut-in manoeuvres, ramps, and exits did not influence the driver. We selected these values based on the average conditions of the control transitions and target speed regulations observed. The results are presented in Fig. 2. Few seconds after the system has been activated (Fig. 2a), drivers showed a higher minimum risk acceptable and a lower maximum risk acceptable (i.e., drivers’ acceptable range with the ACC active is smaller). This means that, immediately after activation, drivers press the gas pedal or increase the target speed when the risk feeling is higher in low risk situations and deactivate or decrease the speed when the risk is lower in high risk situations. Interestingly, drivers who reported a high score on the patient and careful driving style (Fig. 2b) showed a higher minimum risk acceptable and a lower maximum risk acceptable (their acceptable range with the ACC active is smaller). This result means that patient and careful drivers resume manual control or regulate the target

speed when the risk feeling is higher in low risk situations and when it is lower in high risk situations. The driver-specific error term has a different effect on the minimum and on the maximum acceptable risk (Fig. 2c): certain drivers showed a higher risk acceptable in high risk situations and a lower risk acceptable in low risk situations (larger acceptable range with the ACC active), while others showed a higher risk acceptable in high risk situations and a higher risk acceptable in low risk situations (smaller acceptable range with the ACC active). This means that certain drivers, who deactivate or decrease the speed when the risk feeling is higher in high risk situations, can press the gas pedal or increase the target speed in low risk situations when the risk feeling is lower or when it is higher.

6.3.2. ACC system state choice

In low risk situations, the utility functions to overrule the ACC by pressing the gas pedal (AAc), to maintain the system active and increase the target speed (AS+), and not to intervene (AL) are influenced by the driver behaviour characteristics of the subject vehicle and of its leader, and by the functioning of the ACC system as shown in Eqs. (30)–(32):

$$U_n^{AAc}(t) = \alpha^{AAc} + \beta_{TimeAct}^{AAc} \cdot \log(TimeAct(t)) + \beta_{Acc}^{AAc} \cdot Acc(t) + \beta_{AntCutIn3}^{AAc} \cdot AntCutIn3(t) + \gamma^{AAc} \cdot \vartheta_n + \varepsilon_n^{AAc}(t) \quad (30)$$

$$U_n^{AS+}(t) = \beta_{DiffTarSpeed}^{AS+} \cdot DiffTarSpeed(t) + \varepsilon_n^{AS+}(t) \quad (31)$$

$$U_n^{AL}(t) = \alpha^{AL} + \gamma^{I,AL} \cdot \vartheta_n + \varepsilon_n^{AL}(t) \quad (32)$$

where α^{AAc} and α^{AL} are alternative specific constants, $\beta_{TimeAct}^{AAc}$, β_{Acc}^{AAc} , $\beta_{AntCutIn3}^{AAc}$, $\beta_{DiffTarSpeed}^{AS+}$ are the parameters associated with the explanatory variables in Table 4, γ^{AAc} and $\gamma^{I,AL}$ are the parameters associated with the individual-specific error term $\vartheta_n \sim N(0, 1)$, and $\varepsilon_n^{AAc}(t)$, $\varepsilon_n^{AS+}(t)$, and $\varepsilon_n^{AL}(t)$ are i.i.d. Gumbel–distributed error terms. The specification proposed, which includes the alternative not to intervene in low risk situations, resulted in a considerable improvement in goodness of fit compared to a similar specification in which drivers could choose only to overrule the ACC system or to increase the target speed in low risk situations. This means that drivers showed a propensity to maintain the ACC active and do not regulate the target speed in low risk situations. Time after activation, acceleration, and expected cut-ins had a non-significant impact on choices to increase the target speed. The other explanatory variables described in Section 6.2 did not impact significantly the choice to increase the target speed or to overrule the ACC.

Table 4
Estimation results of the continuous-discrete choice model: ACC system state choice.

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

In high risk situations, the utility functions to deactivate the ACC (I) or to decrease the target speed (AS^-) are influenced by the driver behaviour characteristics of the subject vehicle and of its leader, by the functioning of the ACC system, and by characteristics of the freeway segment as shown in Eqs. (33)–(34):

$$U_n^I(t) = \alpha^I + \beta_{DiffTarSpeed}^I \cdot DiffTarSpeed(t) + \beta_{RelAcc}^I \cdot RelAcc(t) + \beta_{OnRamp}^I \cdot OnRamp(t) + \beta_{Exit}^I \cdot Exit(t) + \gamma^{I,AL} \cdot \vartheta_n + \varepsilon_n^I(t) \quad (33)$$

$$U_n^{AS^-}(t) = 0 + \varepsilon_n^{AS^-}(t) \quad (34)$$

where α^I is an alternative specific constant, $\beta_{DiffTarSpeed}^I$, β_{RelAcc}^I , β_{OnRamp}^I , β_{Exit}^I are the parameters associated with the explanatory variables in Table 4, $\gamma^{I,AL}$ is the parameter associated with the individual-specific error term $\vartheta_n \sim N(0, 1)$, and $\varepsilon_n^I(t)$, and $\varepsilon_n^{AS^-}(t)$ are i.i.d. Gumbel – distributed error terms. A similar specification including the alternative not to intervene in high risk situations did not result in a significant improvement in the goodness of fit. This means that drivers showed a more consistent behaviour in high risk situations than in low risk situations. The other explanatory variables in Section 6.2 did not influence significantly the choice to deactivate the ACC.

The estimation results in Table 4 show that, in low risk situations, the alternative specific constant of overruling the ACC system by pressing the gas pedal is non-significant while the alternative specific constant of not intervening is significant and positive. This result means that drivers are more likely not to intervene than to overrule the ACC or to increase the target speed everything else being equal. In high risk situations, the alternative specific constant of deactivating the system is negative. This suggests that drivers are more likely to decrease the target speed than to deactivate the system everything else being equal. In low risk situations, drivers are more likely to increase the ACC target speed when the ACC target speed is lower than the actual speed and to overrule the ACC few seconds after the system has been activated. Drivers are more likely to overrule the system by pressing the gas pedal when the ACC acceleration is low and when they expect cut-ins during the next three seconds. In high risk situations, drivers are more likely to deactivate the ACC when the target speed is lower than the actual speed and when they accelerate more than the leader (negative relative acceleration). In addition, drivers are influenced by the road location and are more likely to deactivate the ACC in proximity to on-ramps, between two ramps, and before exiting the freeway (similar to findings in Pereira et al., 2015). The driver-specific error term has a significant effect on the system state choices in high and low risk situations, meaning that certain drivers are more likely to resume manual control or not to intervene in low risk situations than others. The effect of this term on overruling the ACC was larger than the effect on deactivations and of not intervening in low risk situations, which did not differ significantly. This means that drivers showed a larger variability in overruling the system by pressing the gas pedal.

6.3.3. ACC target speed regulation choice

The regression equations of the ACC target speed increase (Y_n^{TS+}) and decrease (Y_n^{TS-}) are influenced significantly by the target speed set in the system, by the relative speed and by driver characteristics as shown in Eqs. (35)–(36):

$$Y_n^{TS+}(t) = \eta^{TS+} + \xi_{NoviceADAS}^{TS+} \cdot NoviceADAS_n + \varphi_{AAC}^{TS+} \cdot C_{AAC}^{TS+} + \varphi_{AL}^{TS+} \cdot C_{AL}^{TS+} + \gamma^{TS} \cdot \vartheta_n + \omega^{TS+} \cdot \nu_n^{TS+}(t) \quad (35)$$

$$Y_n^{TS-}(t) = \eta^{TS-} + \xi_{DiffTarSpeed}^{TS-} \cdot DiffTarSpeed(t) + \xi_{RelSpeed}^{TS-} \cdot RelSpeed(t) + \varphi_I^{TS-} \cdot C_I^{TS-} + \gamma^{TS} \cdot \vartheta_n + \omega^{TS-} \cdot \nu_n^{TS-}(t) \quad (36)$$

where η^{TS+} and η^{TS-} are constants, $\xi_{NoviceADAS}^{TS+}$, $\xi_{DiffTarSpeed}^{TS-}$, $\xi_{RelSpeed}^{TS-}$ are the parameters associated with the explanatory variables listed in Table 5, φ_{AAC}^{TS+} , φ_{AL}^{TS+} and φ_I^{TS-} are the parameters associated with the selectivity correction terms C_{AAC}^{TS+} , C_{AL}^{TS+} , and C_I^{TS-} , γ^{TS} is the parameter associated with the individual-specific error term $\vartheta_n \sim N(0, 1)$, and ω^{TS+} and ω^{TS-} are the parameters associated with the observation-specific error terms $\nu_n^{TS+}(t) \sim N(0, 1)$ and $\nu_n^{TS-}(t) \sim N(0, 1)$. The logarithmic transformation of the ACC target speed regulation is consistent with the empirical findings and showed a significant improvement in goodness of fit compared to a linear specification. The relative speed and the difference between the target speed and the actual speed did not impact significantly the ACC target speed increments. Experience with ADAS did not influence significantly the target speed decrements. Gender, age, driving styles, workload, and usefulness and satisfaction with ACC did not influence significantly the magnitude of the ACC target speed regulations.

The estimation results in Table 5 show that drivers select a larger ACC target speed decrement when the ACC target speed is higher than the current speed and when they are faster than the leader (negative relative speed). Drivers inexperienced with ADAS prefer smaller ACC target speed increments. The selectivity correction terms have a significant impact on the ACC target speed increments. Drivers choose larger ACC target speed increments in situations in which they are more likely to overrule the system by pressing the gas pedal and less likely not to intervene. This means that, everything else being equal, the magnitude of the increment is positively correlated with the choice probability of overruling the ACC and negatively correlated with the probability of not intervening. The selectivity correction term had a non-significant impact on the target

Table 5

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

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

speed decrement. The driver-specific error term has a significant effect on the magnitude of the target speed regulations, meaning that certain drivers choose larger ACC target speed regulations than others. The effect of this term did not differ significantly between target speed increments and decrements, meaning that drivers show a similar variability in increasing and decreasing the speed. Comparing the impact of the driver-specific error terms on the two levels of decision making, we conclude that drivers who have a smaller acceptable range with ACC active are more likely to resume manual control and to choose larger target speed regulations.

6.3.4. Impact of explanatory variables on the unconditional ACC system choice probabilities and on the magnitude of the ACC target speed regulations

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

The results for ratio variables are presented in Figs. 3 and 4, and for ordinal and nominal variables in Table 6. All findings support the previous interpretations. Comparing the results in Fig. 3, we note that the time after activation, the acceleration (negative), and the driver-specific error term are the variables that have a largest impact on the choice of overruling the system. The difference between the ACC target speed and the actual speed (negative) has the largest impact on the choice of increasing the ACC target speed. The relative speed (negative) and the relative acceleration (negative) have the strongest effect on the choice of deactivating the system. The relative speed (negative) has also the largest impact on the choice of decreasing the ACC target speed. In Table 6, the number of expected cut-ins during the next three seconds has the strongest effect on the probability of deactivations and target speed decrements. In Fig. 4, the difference between the ACC target speed and the actual speed and the relative speed have the largest impact on the magnitude of the target speed decrement.

6.4. Validation analysis

In this section, we analyse the validity of the continuous-discrete choice model presented in Tables 3–5 compared to a choice model that has the same structure and includes only the constants. The aim is to understand the ability of the model to predict the choices of individual drivers on a different road segment and the choices of drivers not included in the estimation sample. The model should be applied to an independent dataset to understand its prediction capability. Since no similar independent datasets are available, two different approaches are proposed: the model is estimated on the

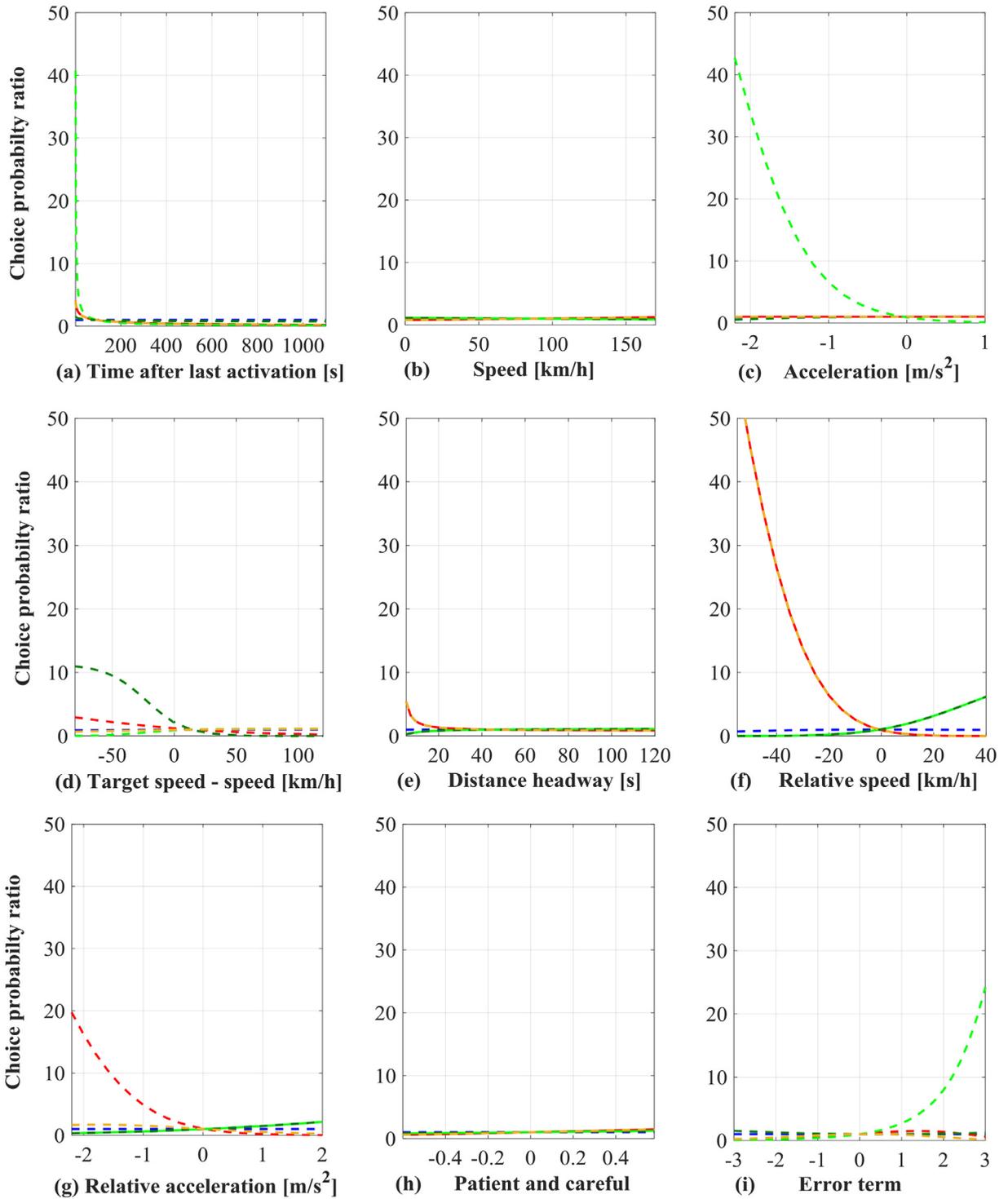


Fig. 3. Impact of the explanatory variables and of the driver-specific error terms on the choice probability ratio (probability predicted divided by probability baseline observation) of transferring to Inactive (red), decreasing the ACC target speed (orange), maintaining the ACC active (blue), increasing the ACC target speed (dark green), and transferring to Active and accelerate (light green). The variables are listed as follows: (a) time after last activation, (b) speed, (c) acceleration, (d) target speed–speed, (e) distance headway, (f) relative speed, (g) relative acceleration, (h) patient and careful driving style (centred on the mean value between drivers), and (i) driver-specific error term. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

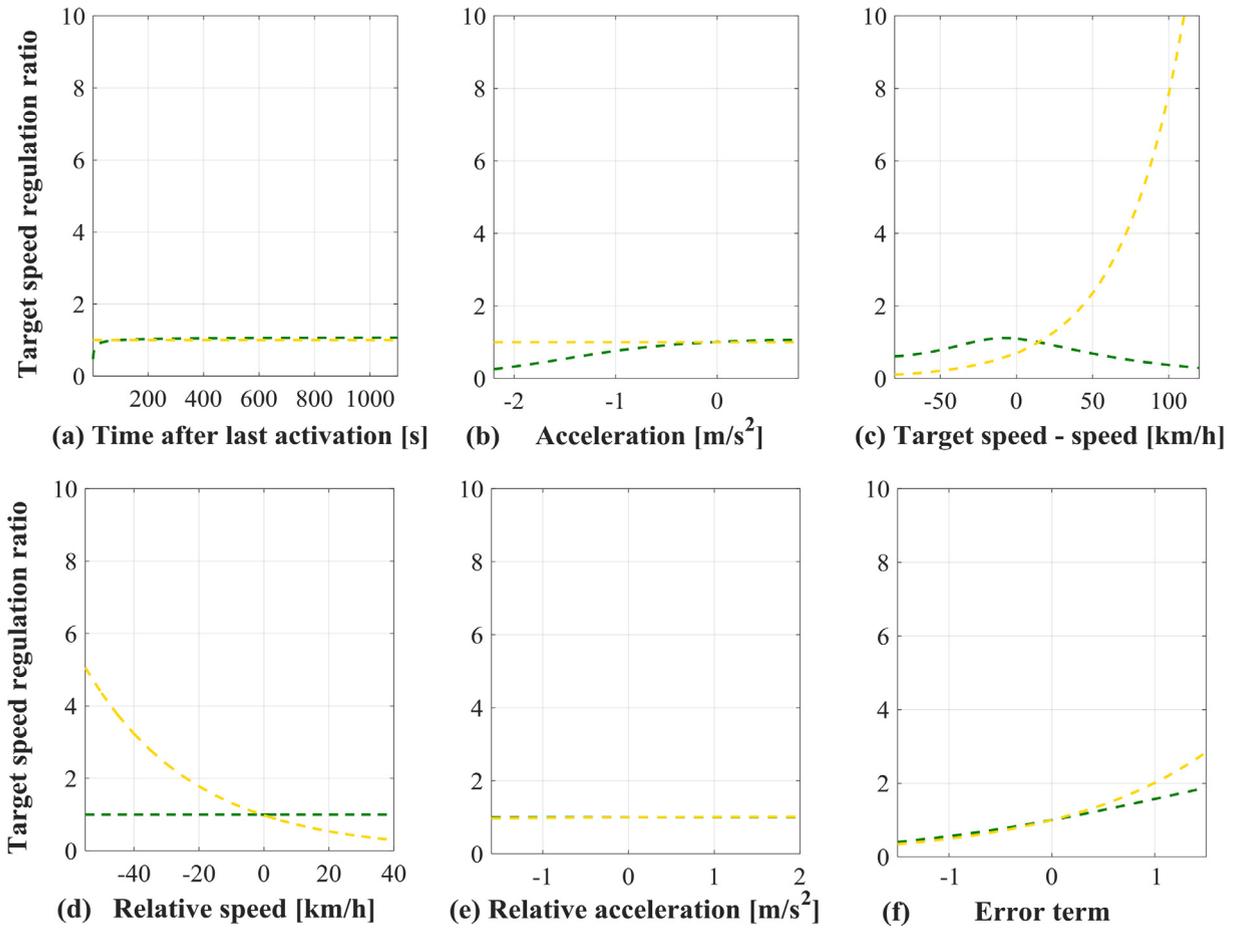


Fig. 4. Impact of the explanatory variables and of the driver-specific error term on the target speed regulation ratio (ACC target speed regulation predicted divided by ACC target speed regulation baseline observation) of decreasing (orange) and increasing (dark green) the ACC target speed. The variables are listed as follows: (a) time after last activation, (b) acceleration, (c) target speed–speed, (d) relative speed, (e) relative acceleration, and (f) driver-specific error term. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 6

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

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

observations of all drivers in two freeway segments and validated on the observations in the freeway segment excluded in the estimation phase (*in-sample-out-of-time*); the model is estimated on the observations of 80% of the drivers in the three freeway segments and validated on the observations of the drivers excluded in the estimation phase (*out-of-sample-in-time*).

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

Table 7

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

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

Note: c denotes the model with constants only, $\hat{\beta}$ the continuous-discrete choice model.**Table 8**

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

	Groups 2–5 vs. group 1	Groups 1, 3–5 vs. group 2	Groups 1–2, 4–5 vs. group 3	Groups 1–3, 5 vs. group 4	Groups 1–4 vs. group 5	M	SD
Drivers	5	4	5	4	5	4.6	0.55
Observations	4742	4687	4658	4758	4723	4714	40.82
$\mathcal{L}(c)$	-818	-622	-679	-651	-749	-704	79.45
$\mathcal{L}(\hat{\beta})$	-734	-564	-589	-590	-681	-632	72.64
$\frac{\mathcal{L}(c) - \mathcal{L}(\hat{\beta})}{\mathcal{L}(c)}$	0.1027	0.0939	0.1333	0.0924	0.091	0.1027	0.0177
$AUC_{tot}(c)$	0.5000	0.5000	0.5000	0.5000	0.5000	0.5000	0
$AUC_{tot}(\hat{\beta})$	0.7688	0.7707	0.8204	0.7799	0.7693	0.7818	0.0197
$RMSE_{TS+}(c)$	1.1163	0.6451	0.7374	0.7925	0.7236	0.8030	0.1636
$RMSE_{TS+}(\hat{\beta})$	1.0853	0.6651	0.7987	0.6804	0.5930	0.7645	0.1735
$\frac{RMSE_{TS+}(c) - RMSE_{TS+}(\hat{\beta})}{RMSE_{TS+}(c)}$	0.0278	-0.0311	-0.0831	0.1414	0.1804	0.0471	0.1001
$RMSE_{TS-}(c)$	1.4753	0.8393	0.7017	1.1174	1.4647	1.1197	0.3158
$RMSE_{TS-}(\hat{\beta})$	1.3555	0.6118	0.6306	1.4024	1.3579	1.0716	0.3682
$\frac{RMSE_{TS-}(c) - RMSE_{TS-}(\hat{\beta})}{RMSE_{TS-}(c)}$	0.0812	0.2711	0.1013	-0.2550	0.0729	0.0543	0.1709

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

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

The final log likelihood, the AUC, and the RMSE of the model with constants only and of the continuous-discrete model on the validation samples are presented in Table 7 (in-sample-out-of-time) and in Table 8 (out-of-sample-in-time). The final log likelihood values indicate that the model proposed has higher forecasting accuracy than the model with constants only both in-sample-out-of-time and out-of-sample-in-time. The AUC shows that the choice component of the model has considerably higher discriminability capabilities than the choice model with constants only. The RMSE indicates that the regression models proposed have lower mean prediction errors than the regressions with constants only but result in larger errors on certain validation samples. Comparing the three freeway segments, we note that the choice model shows large accuracy improvement when it is validated on each segment while both regression models show a reduction in accuracy in the second freeway segment. This result means that, in the second segment, some drivers choose a small (or large) target speed regulation in situations in which the model predicts a large (or small) target speed regulation. This finding might be explained by different geometric characteristics or environmental conditions in the second freeway segment that were not captured by the explanatory variables. Comparing the five groups of drivers, we note that the choice model shows a large accuracy improvement when it is validated on each group, while one of the regression models shows a reduction in accuracy when it is validated on groups 2, 3, and 4. This means that certain drivers in these groups showed a different behaviour in regulating the target speed than the others. Although further analysis is needed to investigate the origin of these differences, we conclude that the continuous-discrete model estimated is useful to predict the decision-making process of individual drivers on a different freeway segment and of drivers not included in the estimation sample.

7. Conclusions and future research

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

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

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

The principal implication of this study is that, to describe driver interaction with ACC, we need a conceptual model framework that connects driver behaviour characteristics, driver characteristics, ACC system settings, and environmental fac-

tors. This conceptual framework can be formulated mathematically using discrete choice models, which are able to capture unobservable constructs and interdependencies between different decisions made by the same driver. Other advantages of discrete choice models are that the model structure can be selected based on insights from driver control theories, the parameters can be formally estimated, and the estimation results are directly interpretable.

The estimation results presented in the case study need to be interpreted with caution. The sample of participants was limited (23) and was not representative of the driver population in terms of gender, age, experience with ADAS, and employment status. It is advised that future studies are carried out with a larger sample of participants that is representative of the driver population. The results of the validation analysis suggest that, to increase the prediction accuracy of the model, future research should investigate more in-depth both driver characteristics and environmental conditions. Moreover, further analysis is needed to generalize the results, which are influenced by the characteristics of the ACC system, to other types of driving assistance systems. Nonetheless, the results in this study have important implications for developing ADAS that are acceptable for drivers in a wider range of traffic situations, and for predicting the impact of different penetration rates of full-range ACC vehicles on traffic flow efficiency and safety.

Full-range ACC systems that mimic human driving style as described by the empirical findings in this study are needed to enhance comfort and acceptability (Bifulco et al., 2013; Goodrich and Boer, 2003). The results suggest the controllers of human-like ACC systems should be designed based on the driver behaviour characteristics of the subject vehicle and its direct leader, on the driver characteristics, and on environmental conditions. It is also advised that these controllers could be calibrated by driving for a short period of time to adapt the parameters to different driving styles and road environments. The choice model based on feeling of risk and task difficulty can be directly implemented into the system to identify the situations in which drivers are likely to resume manual control. Accounting for a certain variability in drivers' decision making, the model can also be used to forecast the probability that drivers resume manual control based on the programmed response of the system. 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 simulations that include the empirical results in this study are needed to evaluate precisely the impacts of full-range ACC on traffic safety and traffic flow efficiency. The findings have shown that there are large differences between and within drivers in the same traffic situation, which can be explained by the functioning of the system, observed and unobserved driver characteristics, and environmental conditions. All these factors should be included into microscopic traffic flow models. The choice model can be directly implemented into a microscopic simulation package and is expected to result in more accurate predictions than the models available. Previous microscopic traffic simulation models have proposed deterministic decision rules for resuming manual control in ACC, which were not supported by current theories of driver behaviour and were not estimated based on empirical data. The possibility of regulating the longitudinal control task by adjusting the ACC target speed was ignored. These methodological limitations were addressed in the current study. The data collection method proposed (controlled on-road experiment) allows analysing driving behaviour with full-range ACC in real traffic, controlling for potentially confounding factors such as road design and traffic conditions. In addition, the driver characteristics collected using the questionnaires contributed to explain the observed behaviour.

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

Acknowledgements

Silvia Varotto, Haneen Farah, Bart van Arem and Serge Hoogendoorn were funded by the Marie Curie Initial Training Network through the project HFAuto—Human Factors of Automated Driving (FP7-PEOPLE-2013-ITN, grant 605817), while Tomer Toledo was supported by the Israeli Ministry of National Infrastructure, Energy and Water Resources. The authors are grateful to Klaus Bogenberger at Universität der Bundeswehr in Munich for his valuable contribution in designing the experiment, and Werner Huber, Pei-Shih (Dennis) Huang and Martin Friedl at BMW group in Munich for their appreciated technical support in collecting the data. Special thanks to Michel Bierlaire at Ecole Polytechnique Fédérale de Lausanne, Cinzia Cirillo at University of Maryland, Moshe Ben-Akiva at Massachusetts Institute of Technology, and Kenneth Train at University of California Berkeley for insightful comments which contributed to improve the model specification and the validation. Finally, the authors thank two anonymous reviewers for their valuable feedback on the paper.

Appendix A. Data analysis

Figs. A1 and A2.

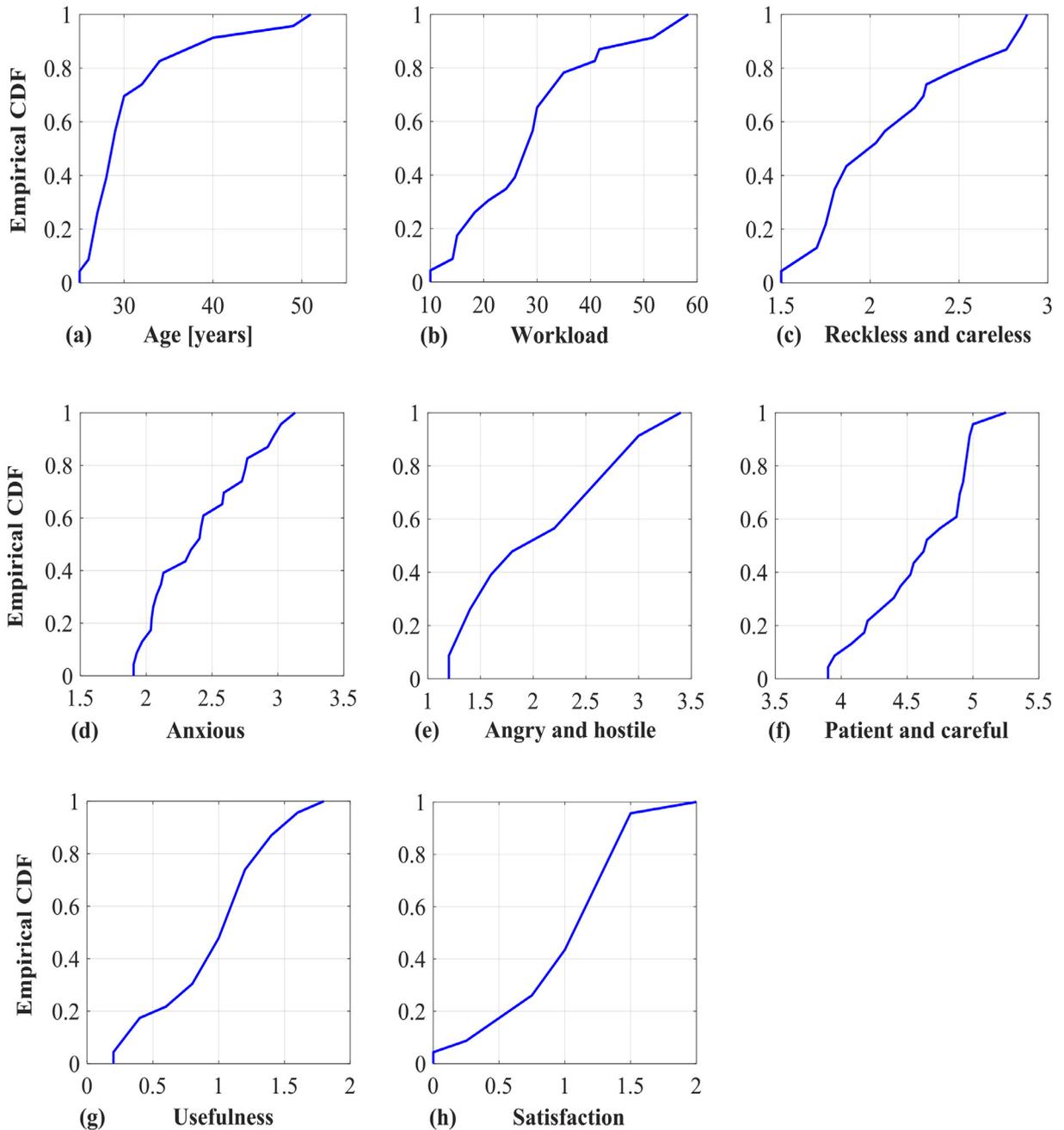


Fig. A1. Empirical cumulative distribution functions of the driver characteristics (continuous variables): (a) age, (b) workload (Byers et al., 1989; Kyriakidis et al., 2014), (c) reckless and careless driving style, (d) anxious driving style, (e) angry and hostile driving style, (f) patient and careful driving style (Taubman-Ben-Ari et al., 2004), (g) usefulness, and (h) satisfaction (Kyriakidis et al., 2014; Van der Laan et al., 1997). The workload is scored on a scale from 0 to 100, the driving styles on a scale from 1 to 6, and usefulness and satisfaction on a scale from -2 to 2.

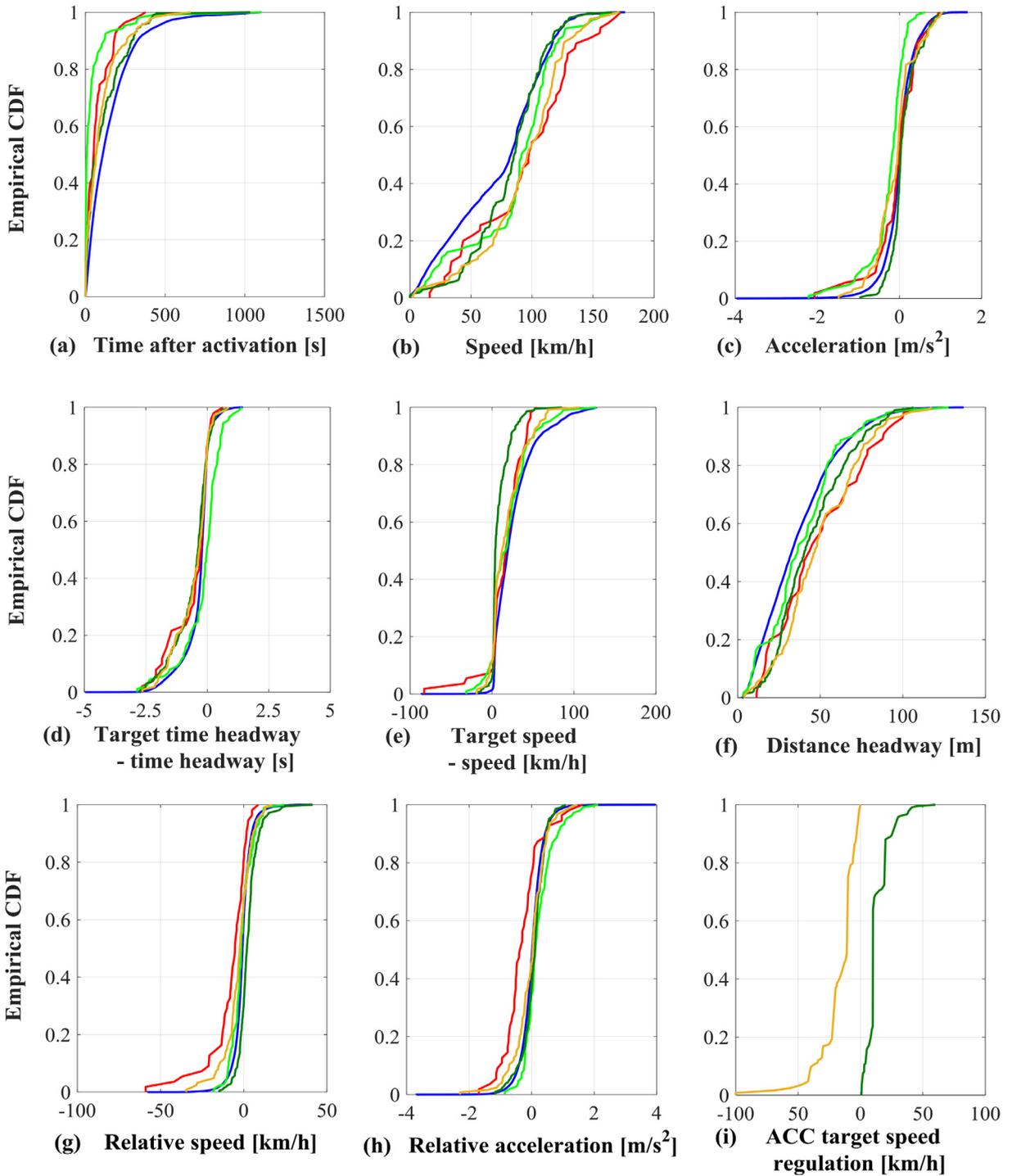


Fig. A2. Empirical cumulative distribution functions of the driver behaviour characteristics of transferring to Inactive (red), decreasing the ACC target speed (orange), maintaining the ACC active (blue), increasing the ACC target speed (dark green), and transferring to Active and accelerate (light green). The variables are listed as follows: (a) time after last activation, (b) speed, (c) acceleration, (d) target time headway–time headway, (e) target speed–speed, (f) distance headway, (g) relative speed, (h) relative acceleration, and (i) ACC target speed regulation. A reduced version of the figure focusing on transitions to manual control was presented in [Varotto et al. \(2017\)](#). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table A1

Two sample Kolmogorov-Smirnov test (p-value) of the driver behaviour characteristics when drivers transfer the ACC to Inactive (I), decrease the ACC target speed (AS-), maintain the ACC Active (A), increase the ACC target speed (AS+), and transfer to Active and accelerate (AAC); a reduced version of the table focusing on transitions to manual control was presented in Varotto et al. (2017).

Variables	I vs. AS-	I vs. A	I vs. AAC	AS- vs. A	AS- vs. AS+	AS+ vs. A	AS+ vs. AAC	AAC vs. A
Time after last activation	0.254(**)	4.10·10 ⁻⁵	8.64·10 ⁻⁵	0.000354	0.301(**)	4.10·10 ⁻⁶	3.04·10 ⁻¹⁰	5.78·10 ⁻²⁷
Speed	0.320(**)	0.00107	0.0486(*)	1.16·10 ⁻⁵	0.000212	3.02·10 ⁻⁷	0.0182(*)	4.27·10 ⁻⁵
Acceleration	0.438(**)	0.428(**)	0.00320	0.000546	2.43·10 ⁻⁵	0.00189	5.70·10 ⁻¹³	2.19·10 ⁻¹⁰
Target time headway–time headway	0.900(**)	0.185(**)	0.000110	0.00149	0.424(**)	2.01·10 ⁻⁸	0.0905(**)	1.74·10 ⁻¹¹
Target speed–speed	0.613(**)	0.228(**)	0.464(**)	0.00214	3.36·10 ⁻⁵	8.66·10 ⁻²⁹	5.99·10 ⁻⁹	0.00496
Distance headway	0.781(**)	0.00837	0.0335(*)	1.69·10 ⁻⁸	0.121(**)	3.69·10 ⁻⁸	1.17·10 ⁻⁶	0.128(**)
Relative speed	0.0680(**)	2.83·10 ⁻⁸	0.000230	3.26·10 ⁻⁵	1.94·10 ⁻¹⁰	1.34·10 ⁻¹⁷	1.30·10 ⁻⁸	0.0952(**)
Relative acceleration	0.000485	1.17·10 ⁻⁸	7.67·10 ⁻⁹	0.0694(**)	0.0296(*)	0.000271	0.0626(**)	0.00108

**p-value > 0.05; * 0.01 < p-value < 0.05.

References

- Alkim, T.P., Bootsma, G., Hoogendoorn, S.P., 2007. Field operational test "the assisted driver". In: IEEE Intelligent Vehicles Symposium. Istanbul, pp. 1198–1203.
- Bierlaire, M., 2016. PythonBiogeme: a short introduction. In: TRANSP-OR (Ed.), Biogeme. Transport and Mobility Laboratory, School of Architecture, Civil and Environmental Engineering, Ecole Polytechnique Fédérale de Lausanne, Lausanne.
- Bifulco, G.N., Pariota, L., Simonelli, F., Di Pace, R., 2013. Development and testing of a fully adaptive cruise control system. *Transp. Res. Part C* 29, 156–170.
- Byers, J.C., Bittner, A.C., Hill, S.G., 1989. Traditional and raw task load index (TLX) correlations: are paired comparisons necessary? *Adv. Ind. Ergon. Saf.* 1 481–485.
- Castro, M., Paletti, R., Bhat, C.R., 2013. A spatial generalized ordered response model to examine highway crash injury severity. *Accid. Anal. Prev.* 52, 188–203.
- Choudhury, C., 2007. Modeling driving decisions with latent plans. *Civil and Environmental Engineering*, Massachusetts Institute of Technology.
- Choudhury, C., Ben-Akiva, M., Toledo, T., Rao, A., Lee, G., 2007. State dependence in lane changing models. *ISTTT International Symposium on Transportation and Traffic Theory*.
- Danaf, M., Abou-Zeid, M., Kaysi, I., 2015. Modeling anger and aggressive driving behavior in a dynamic choice-latent variable model. *Accid. Anal. Prev.* 75, 105–118.
- Dubin, J.A., McFadden, D.L., 1984. An econometric analysis of residential electric appliance holdings and consumption. *Econometrica* 52, 345–362.
- Eluru, N., Bhat, C.R., Hensher, D.A., 2008. A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. *Accid. Anal. Prev.* 40, 1033–1054.
- European Commission, 2017. Cooperative Intelligent Transport Systems, C-ITS Platform Phase II.
- Farah, H., Toledo, T., 2010. Passing behavior on two-lane highways. *Transp. Res. Part F* 13, 355–364.
- Fawcett, T., 2006. An introduction to ROC analysis. *Pattern Recognit. Lett.* 27, 861–874.
- FGSV, 2008. Richtlinie Für Die Anlage von Autobahnen (RAA). In: *Verkehrswesen, F.f.S.-u. (Ed.), Richtlinie Für Die Anlage von Autobahnen (RAA)*. FGSV - Verlag, Köln.
- Fuller, R., 2000. The task-capability interface model of the driving process. *Recherche - Transports - Sécurité* 66, 47–57.
- Fuller, R., 2002. Human factors and driving. In: Fuller, R., Santos, J.A. (Eds.), *Human Factors for Highway Engineers*. Emerald, Bingley.
- Fuller, R., 2005. Towards a general theory of driver behaviour. *Accid. Anal. Prev.* 37, 461–472.
- Fuller, R., 2011. Driver control theory: from task difficulty homeostasis to risk allostasis. In: Porter, B.E. (Ed.), *Handbook of Traffic Psychology*. Elsevier, pp. 13–26.
- Fuller, R., McHugh, C., Pender, S., 2008. Task difficulty and risk in the determination of driver behaviour. *Eur. Rev. Appl. Psychol.* 58, 13–21.
- Fuller, R., Santos, J.A., 2002. Psychology and the highway engineer. In: Fuller, R., Santos, J.A. (Eds.), *Human Factors for Highway Engineers*. Emerald, Bingley, pp. 1–10.
- Goodrich, M.A., Boer, E.R., 2003. Model-based human-centered task automation: a case study in ACC system design. *IEEE Trans. Syst. Man Cybern. Part A* 33, 325–336.
- Greene, W., Gillman, M., Harris, M.N., Spencer, C., 2013. The tempered ordered probit (top) model with an application to monetary policy. *Discussion Paper Series 2013-10*. Department of Economics, Loughborough University.
- Greene, W.H., Hensher, D.A., 2009. *Modeling Ordered Choices*. Cambridge University Press.
- Greene, W.H., Hensher, D.A., 2010. Ordered choices and heterogeneity in attribute processing. *J. Transport Econ. Policy* 44, 331–364.
- Hamdar, S.H., Mahmassani, H.S., Treiber, M., 2015. From behavioral psychology to acceleration modeling: calibration, validation, and exploration of drivers' cognitive and safety parameters in a risk-taking environment. *Transp. Res. Part B* 78, 32–53.
- Hand, D.J., Till, R.J., 2001. A simple generalization of the area under the ROC curve to multiple class classification problems. *Mach. Learn.* 45, 171–186.
- Hastie, T., Tibshirani, R., Friedman, J., 2009. *The Elements of Statistical Learning: Data mining, Inference and Prediction*. Springer.
- Hess, S., Train, K., Polak, J., 2006. On the use of modified Latin hyper-cube sampling (MLHS) method in the estimation of mixed logit model for vehicle choice. *Transp. Res. Part B* 40, 147–163.
- Hoogendoorn, R., Van Arem, B., Hoogendoorn, S.P., 2013. Incorporating driver distraction in car-following models: applying the TCI to the IDM. *16th International IEEE Annual Conference on Intelligent Transportation Systems (ITSC)*.
- Hoogendoorn, R., van Arem, B., Hoogendoorn, S.P., 2014. Automated driving, traffic flow efficiency, and human factors: literature review. *Transp. Res. Record* 2422, 113–120.
- Klunder, G., Li, M., Minderhoud, M., 2009. Traffic flow impacts of adaptive cruise control deactivation and (Re) activation with cooperative driver behavior. *Transp. Res. Record* 2129, 145–151.
- Koutsopoulos, H.N., Farah, H., 2012. Latent class model for car following behavior. *Transp. Res. Part B* 46, 563–578.
- Kyriakidis, M., de Winter, J.C., Happee, R., 2014. Human Factors of Automated Driving – Recommended Questionnaires.
- Lewis-Evans, B., De Waard, D., Brookhuis, K.A., 2010. That's close enough: a threshold effect of time headway on the experience of risk, task difficulty, effort, and comfort. *Accid. Anal. Prev.* 42, 1926–1933.
- Lewis-Evans, B., Rothengatter, T., 2009. Task difficulty, risk, effort and comfort in a simulated driving task—implications for risk Allostasis theory. *Accid. Anal. Prev.* 41, 1053–1063.
- Lu, Z., Happee, R., Cabral, C.D.D., Kyriakidis, M., de Winter, J.C.F., 2016. Human factors of transitions in automated driving: a general framework and literature survey. *Transp. Res. Part F* 43, 183–198.
- Malta, L., Ljung Aust, M., Faber, F., Met, B., Saint Pierre, G., Benmimoun, M., Schafer, R., 2012. EuroFOT Final Results: Impacts on Traffic Safety.
- Martens, M.H., Jenssen, G.D., 2012. Behavioral adaptation and acceptance. In: Eskandarian, A. (Ed.), *Handbook of Intelligent Vehicles*. Springer-Verlag, London, pp. 117–138.

- Michon, J.A., 1985. A critical view of driver behavior models: what do we know, what should we do? In: Evans, L., Schwing, R. (Eds.) *Human Behavior and Traffic Safety*. Plenum Press, New York, NY, USA, pp. 485–520.
- Näätänen, R., Summala, H., 1974. A model for the role of motivational factors in drivers' decision-making. *Accident Anal. Prevent.* 6, 243–261.
- NHTSA, 2005. *Automotive Collision Avoidance System Field Operational Test Report: Methodology and Results*. National Highway Traffic Safety Administration, U.S. Department of Transportation.
- Pauwelussen, J., Feenstra, P.J., 2010. Driver behavior analysis during ACC activation and deactivation in a real traffic environment. *IEEE Trans. Intell. Transp. Syst.* 11, 320–338.
- Pereira, M., Beggiato, M., Petzoldt, T., 2015. Use of adaptive cruise control functions on motorways and urban roads: changes over time in an on-road study. *Appl. Ergon.* 50, 105–112.
- Ranney, T.A., 1994. Models of driving behavior: a review of their evolution. *Accident Anal. Prevent.* 26, 733–750.
- Rothengatter, T., 2002. Drivers' illusions—no more risk. *Transp. Res. Part F* 5, 249–258.
- Saifuzzaman, M., Zheng, Z., 2014. Incorporating human-factors in car-following models: a review of recent developments and research needs. *Transp. Res. Part C* 48, 379–403.
- Saifuzzaman, M., Zheng, Z., Mazharul Haque, M., Washington, S., 2015. Revisiting the task-capability interface model for incorporating human factors into car-following models. *Transp. Res. Part B* 82, 1–19.
- Schakel, W.J., Gorter, C.M., De Winter, J.C.F., Van Arem, B., 2017. Driving characteristics and adaptive cruise control—a naturalistic driving study. *IEEE Intell. Transp. Syst. Mag.* 9, 17–24.
- Summala, H., 1988. Risk control is not risk adjustment: the zero risk theory of driver behaviour and its implications. *Ergonomics* 31, 491–506.
- Summala, H., 2007. Towards understanding motivational and emotional factors in driver behaviour: comfort through satisficing. In: Cacciabue, P. (Ed.), *Modelling Driver Behaviour in Automotive Environments: Critical Issues in Driver Interactions With Intelligent Transport Systems*. Springer-Verlag, London, pp. 189–207.
- Taubman-Ben-Ari, O., Mikulincer, M., Gillath, O., 2004. The multidimensional driving style inventory—scale construct and validation. *Accident Anal. Prevent.* 36, 323–332.
- Toledo, T., 2003. *Integrated driving behavior modeling*. Civil and Environmental Engineering. Massachusetts Institute of Technology, Boston.
- Toledo, T., Koutsopoulos, H.N., Ben-Akiva, M., 2007. Integrated driving behavior modeling. *Transp. Res. Part C* 2007, 96–112.
- Toledo, T., Koutsopoulos, H.N., Ben-Akiva, M.E., 2009. Estimation of an integrated driving behavior model. *Transp. Res. Part C* 17, 365–380.
- Train, K., 1986. *Continuous/discrete models. Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand*. MIT Press, Cambridge.
- Vaa, T., 2007. *Modelling driver behaviour on basis of emotions and feelings: intelligent transport systems and behavioural adaptations*. In: Cacciabue, P. (Ed.), *Modelling Driver Behaviour in Automotive environments: Critical issues in Driver Interactions With Intelligent Transport Systems*. Springer-Verlag, London, pp. 208–232.
- Van Arem, B., De Vos, A.P., Vanderschuren, M.J.W.A., 1997. *The Microscopic Traffic Simulation Model MIXIC 1.3*. TNO Inro, Delft.
- Van der Laan, J.D., Heino, A., De Waard, D., 1997. A simple procedure for the assessment of acceptance of advanced transport telematics. *Transp. Res. Part C* 5, 1–10.
- Van Driel, C., Van Arem, B., 2010. The impact of a congestion assistant on traffic flow efficiency and safety in congested traffic caused by a lane drop. *J. Intell. Transp. Syst.* 14, 197–208.
- Varotto, S.F., Farah, H., Toledo, T., van Arem, B., Hoogendoorn, S.P., 2017. Resuming manual control or not? Modelling choices of control transitions in full-range adaptive cruise control. *Transp. Res. Record* 2622, 38–47.
- Varotto, S.F., Hoogendoorn, R.G., van Arem, B., Hoogendoorn, S.P., 2014. Human factors of automated driving: predicting the effects of authority transitions on traffic flow efficiency. 2nd TRAIL Internal Congress.
- Varotto, S.F., Hoogendoorn, R.G., van Arem, B., Hoogendoorn, S.P., 2015. Empirical longitudinal driving behavior in authority transitions between adaptive cruise control and manual driving. *Transp. Res. Record* 2489, 105–114.
- Vij, A., Walker, J.L., 2016. How, when and why integrated choice and latent variable models are latently useful. *Transp. Res. Part B* 90, 192–217.
- Viti, F., Hoogendoorn, S.P., Alkim, T.P., Bootsma, G., 2008. Driving behavior interaction with ACC: results from a Field Operational Test in the Netherlands. *IEEE Intelligent Vehicles Symposium*.
- Vlakveld, W., Vissers, L., Hulleman, K., Van Nes, N., 2015. *An Empirical Exploration of the Impact of Control Transitions on Situation Awareness For Potential Hazards*. SWOV Institute for Road Safety Research The Hague, The Netherlands.
- Walker, J.L., 2001. *Extended Discrete Choice Models: Integrated Framework, Flexible Error Structures, and Latent Variables*. Civil and Environmental Engineering. Massachusetts Institute of Technology, Boston.
- Wilde, G.J.S., 1982. The theory of RHT: implications for safety and health. *Risk Anal.* 2, 209–226.
- Xiao, L., Wang, M., Van Arem, B., 2017. Realistic car-following models for microscopic simulation of adaptive and cooperative adaptive cruise control vehicles. *Transp. Res. Record* 2623, 1–9.
- Xiong, H., Boyle, L.N., 2012. Drivers' adaptation to adaptive cruise control: examination of automatic and manual braking. *IEEE Trans. Intell. Transp. Syst.* 13, 1468–1473.