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How do drivers respond to silent automation failures? Driving simulator study and comparison of computational driver braking models

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Précis

This article presents novel computational models predicting drivers' brake reaction times to lead vehicle braking, during driving with CC and ACC, when the latter silently fails. The predictions of the computational driver models were validated using the data from a driving simulator study and compared between them using the AIC.

Running head

Drivers response to automation failures

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Abstract

Objective

This paper aims to describe and test novel computational driver models, predicting drivers' brake reaction times (BRTs) to different levels of lead vehicle braking, during driving with Cruise Control (CC) and during silent failures of Adaptive Cruise Control (ACC).

Background

Validated computational models predicting BRTs to silent failures of automation are lacking but are important for assessing safety benefits of automated driving.

Method

Two alternative models of driver response to silent ACC failures are proposed: a looming prediction model, assuming that drivers embody a generative model of ACC, and a lower gain model, assuming that drivers' arousal decreases due to monitoring of the automated system. Predictions of BRTs issued by the models were tested using a driving simulator study.

Results

The driving simulator study confirmed the predictions of the models: a) BRTs were significantly shorter with an increase in kinematic criticality, both during driving with CC and ACC; b) BRTs were significantly delayed when driving with ACC compared to driving with CC. However, the predicted BRTs were longer than the ones observed, entailing a fitting of the models to the data from the study.

Conclusion

Both the looming prediction model and the lower gain model predict well the BRTs for the ACC driving condition. However, the looming prediction model has the advantage of being able to predict average BRTs using the exact same parameters as the model fitted to the CC driving data.

Application

Knowledge resulting from this research can be helpful for assessing safety benefits of automated driving.

Keywords

Adaptive Cruise Control; Autonomous driving; Cruise Control; Driver models; Visual looming.

1. Introduction

Human limitations are widely recognized as a main contributing factor to road crashes (Hendricks et al., 2001; Treat et al., 1979) and the introduction of automated driving is expected to address this issue by automating the driving task (Victor et al., 2017). The degrees of automation for on-road vehicles are classified by the Society of Automotive Engineers (SAE, 2018) into different levels, from manual driving up to full driving automation. At the highest levels (4-5), the automated driving system (ADS) should perform the entire dynamic driving task (DDT), without any expectation that a user will respond to a request to intervene. However, at lower levels, the driver is either expected to be receptive to ADS' request to intervene (level 3) or to supervise the driving automation system[1] (level 1 and level 2).

Existing research has warned about possible human factors issues associated to the supervisory role of the driver, including among others skill degradation (Skottke et al., 2014), complacency (Payre et al., 2016) and negative behavioral adaptations (Jamson et al., 2013; Reimer et al., 2016). Given that automated vehicles may fail (Dikmen & Burns, 2016), a relevant question is how drivers will react in those situations. Many previous studies have investigated driver response to takeover requests from the automated vehicle (Gold et al., 2018) and to a lesser extent also driver responses to silent failures, where the automation fails without alerting the driver (Blommer et al., 2017; Strand et al., 2012; Young & Stanton, 2007).

Given a detailed enough understanding of drivers' reaction to automation silent failures, it is possible to develop computational driver models that can be used to assess the safety benefits of driving automation systems (Bärgman et al., 2017; Kusano & Gabler, 2012; McLaughin et al., 2008). To our knowledge, computational driver models describing drivers' reactions to automation silent failures are lacking, exception made for the model developed by Seppelt & Lee (2015): however, this model is limited in that it only predicts an expected average brake reaction time (BRT) for a given kinematical scenario, not full BRT distributions, and it also does not predict BRTs for manual driving. Therefore, the current paper aims to:

1. Present three computational driver models predicting full probability distributions for BRTs in lead vehicle braking scenarios, across different kinematic conditions, both during driving with Cruise Control (CC) and driving with Adaptive Cruise Control (ACC), when the latter silently fails.
2. Show the results from a driving simulator study conducted to test the predictions of the computational driver models.

[1] For a detailed definition of an automated driving system (ADS) and a driving automation system, please refer to the recommended practice SAE J3016 (SAE, 2018)

3. Carry out a detailed comparison of the three computational driver models, after fitting them to the driving simulator data.

2. Models of driver response in manual and automated mode

2.1 Models' descriptions

The classical view of drivers' reactions to critical traffic events heavily relies on the concept of reaction time (Green 2000; Olson 1989; Olson & Sivak 1986), often considered a property of the individual driver, and potentially influenced by age, expectancy, and other factors (Barrett et al., 1968; Fambro et al., 1998; Green, 2000; Muttart, 2003; Muttart, 2005). However, recent experimental (Ljung Aust et al., 2013) as well as naturalistic (Markkula et al. 2016a; Victor et al. 2015) data suggest that the timing of driver reactions in unexpected emergency situations is to a large extent also determined by the situation kinematics (Engström, 2010). Such kinematics dependence of driver reaction timing has also been experimentally demonstrated in automation take-over situations (Gold et al., 2018).

The kinematics of a driving scenario translates into patterns of optical flow as well as perceptual inputs in non-visual modalities, such as kinesthetic and tactile cues (Flach et al., 2004). In rear-end scenarios, the kinematics of the lead vehicle is reflected by its optical expansion on the retina of the following driver (looming). For example, the quantity τ – calculated as the optical angle subtended by the lead vehicle, θ, divided by the angular rate of expansion, $\dot{\theta}$ – provides an estimation of time-to-collision (Lee, 1976), as reported below:

$$\tau = \frac{\theta}{\dot{\theta}} \qquad (1)$$

Several models of driver reactions in rear-end scenarios have been developed based on these ideas (Flach et al., 2004; Markkula, 2014; Markkula et al., 2016; Markkula & Engström, 2017; Engström et al., 2017; Venkatraman et al., 2016; Svärd et al., 2017). More specifically, these models suggest that drivers react after some fixed looming threshold, or after accumulation (integration) of the looming signal to a threshold, potentially also together with other perceptual cues such as brake lights (Markkula, 2014; Engström et al., 2017; Xue et al., 2018). The accumulation of the looming signal was included in the model by Svärd et al. (2017), based on a framework by Markkula (Markkula, 2014; Markkula et al., 2018), but this model also assumed that drivers in emergency rear-end situations react to unexpected looming rather than to looming per se (Engström et al., 2018). The unexpected looming can be understood as the discrepancy between the predicted and actual looming, that is, the looming prediction error. This idea aligns with the broader framework known as predictive processing that has recently become a major force in neuroscience and cognitive science (e.g., Clark, 2013; Clark, 2016; Friston et al., 2010).

The accumulative part of the driver reaction model described by Svärd et al. (2017) has the following form:

$$\frac{dA}{dt} = k\varepsilon(t) - m + \nu(t) \qquad (2)$$

where *ε(t)* is the looming prediction error, k and m are free model parameters, and braking is initiated once A exceeds a threshold, set to one. Variability is included in the model using $\nu(t)$, a zero-mean Gaussian noise signal with standard deviation $\sigma\sqrt{\Delta t}$ for a simulation time step Δt. The looming prediction error is given by:

$$\varepsilon(t) = \tau_a^{-1}(t) - \tau_p^{-1}(t) \qquad (3)$$

where τ_a^{-1} refers to the actual looming (inverse tau) signal and τ_p^{-1} to the predicted looming. The parameter k in Equation 2 can be interpreted as the gain determining the impact of the prediction error on the accumulator while m can be interpreted as the sum of all non-looming evidence for and against the need of braking (Svärd et al., 2017; Markkula, 2014).

The models proposed in the current paper directly use the formulation by Svärd et al. (2017) for scenarios where the driver is driving with CC. For scenarios where the driver is driving with ACC and the system has a silent failure, two alternative (but not necessarily mutually exclusive) extensions of the model by Svärd et al. (2017) are proposed:

1. Looming prediction model: in this model, it is assumed that the driver continuously predicts the looming that would arise from a properly functioning ACC, in response to a decelerating lead vehicle, and what is being accumulated in the braking decision

process are deviations from this prediction. For simplicity, the predictions are here computed assuming that the driver has a perfect mental representation of the ACC working principle, that is, the driver embodies a perfect generative model (Friston et al., 2010) of how looming cues are generated by the ACC.

2. Lower gain model: in this model, it is assumed that a decrease in driver arousal occurs due to the monitoring of the ACC, sometimes referred to in terms of passive fatigue (Desmond & Hancock, 2001; Greenlee et al., 2018; Saxby et al., 2013). It has been shown that empirically observed effects on response times of increases and decreases in arousal can be well accounted for by increases and decreases in the accumulation gain k in evidence accumulation models (Jepma et al., 2008; Markkula & Engström, 2017; Ratcliff & Van Dongen, 2011).

The next section describes the a priori predictions of BRTs obtained from these models.

2.2. A priori model predictions of BRTs

We applied the computational driver models in simulations to make initial predictions about the brake reaction times (BRTs) in rear-end conflicts, during driving with CC – henceforward referred as manual mode – and ACC – henceforth referred as driver assistance mode. The simulations aimed to reproduce a typical highway driving scenario, and the same scenario was also used in the driving simulator study described later. Each simulation started with the modelled driver driving either manually or with engaged ACC, at a speed of 100 km/h and keeping a time headway to the lead vehicle of 2.5 seconds. The lead vehicle, initially travelling at 100 km/h, applied a constant deceleration which was varied, between simulations, in the 2.5 - 4.5 m/s^2 range. During driving with engaged ACC, the system had a silent failure when the lead vehicle started to decelerate.

To predict BRTs during driving in manual mode, we implemented a deterministic (σ = 0) looming accumulator model (hereafter named manual driving model), based on Equations 1-3. A key challenge in the parametrization was that the model should represent driver reactions in truly surprising situations with different kinematics. Since each study participant can only be truly surprised in the first exposure of the critical scenario, there exists no single dataset with a sufficient number of driver reaction data points for a range of kinematics. However, there exists a set of published lead vehicle studies that implemented a similar lead vehicle braking scenario with different kinematics, where the first braking event was designed to be truly surprising to the participant. Among these studies, we selected research experiments (Engström et al., 2010; Ljung Aust et al., 2012; Markkula et al., 2013; Markkula et al., 2016; Nilsson et al., 2018) where we had full access to the dataset and where the kinematics (initial speeds, time headway and lead vehicle deceleration rates) differed between the studies. These studies also differed somewhat in other aspects of their methodology and experimental conditions (e.g., vehicle type, type of driving simulator and driver characteristics) but were deemed to be sufficiently similar for the parametrization of the present reaction model. The common lead vehicle (LV) braking scenario used in these studies involved a vehicle overtaking the subject vehicle (SV) and then cutting in front. After the cut-in, the LV continued to accelerate away from the SV before suddenly braking at a predefined time headway with a set deceleration rate. In this way, the kinematics at lead vehicle brake onset could be controlled with a high degree of precision. In two of the studies (Ljung Aust et al., 2013; Nilsson et al., 2018), the LV speed was instantaneously reset (to SV's speed or a lower value respectively) at LV brake onset. The kinematic parameter values and observed average BRTs are given in Table 1 (for more details, please see the individual publications).

Table 1: Scenario parameters and observed BRT values for the driving simulator studies used for the model parametrization

Study	Number of participants	SV type	SV instructed initial speed [km/h]	LV initial speed [km/h]	Initial THW [s]	LV deceleration [g]	Observed average BRT [s]
Engström et al. (2010)	20	Car	70	80	1.5	0.51	2.18
Ljung Aust et al. (2013)	8	Car	90	90	2.5	0.55	3.16

Markkula et al. (2013)	48	Truck	80	80	1.5	0.35	1.82
Nilsson et al., (2018)	10	Car	80	48	1.3	0.6	1.04
Markkula et. al (2016)	46	Truck	90	90	5	0.92	3.32

The first braking events for each of the five studies reported in Table 1 were used for the parameterization. Moreover, while some of the studies involved conditions with cognitively loading secondary tasks, only data from the no task (baseline) conditions were used. We implemented the respective scenarios in simulation and searched for the values of the model parameters k and m which best fitted the BRT averages reported in each study in terms of the coefficient of determination, R^2 (Field, 2009). It was found that varying m did not make a strong contribution and, with m = 0, the maximum R^2 of 0.77 was obtained for k = 2.7. This relatively high R^2 value, suggesting that almost 80% of the variance in the observed BRT values is explained by the model, supports the pooling of data from different studies for the present model parameterization.

In the manual driving model, the driver does not expect any initial looming ($\tau_p^{-1} = 0$) and, therefore, the looming prediction error equals the actual looming (dashed line in Figure 1) and increases sharply when the lead vehicle decelerates. The corresponding predicted drivers' braking response is shown as a blue vertical line in Figure 1.

For the predictions of BRTs during driving in driver assistance mode, we implemented computational versions of the looming prediction model and the lower gain model described earlier.

In the looming prediction model, the values of the model parameters were the same as in the manual driving model (k = 2.7, m = 0 and σ = 0). However, while $\tau_p^{-1} = 0$ (no expected looming) in the manual driving model, in the looming prediction model, τ_p^{-1} was the looming that would have been generated in the scenario, had the ACC braked (dotted line in Figure 1).

This model thus sees a smaller looming prediction error (solid line in Figure 1) than the manual driving model, and consequently the driver reacts later (red vertical line in Figure 1).

The lower gain model assumes a change in gain k. Here, k = 1.1 was chosen to obtain BRTs roughly comparable to those of the looming prediction model. The remaining parameters (m = 0 and σ = 0) and the calculation of the looming prediction error (Equation 3) were the same as in the manual driving model, that is the driver did not expect any initial looming ($\tau_p^{-1} = 0$). However, due to the lower gain, also in this model the driver reacts later (magenta vertical line in Figure 1).

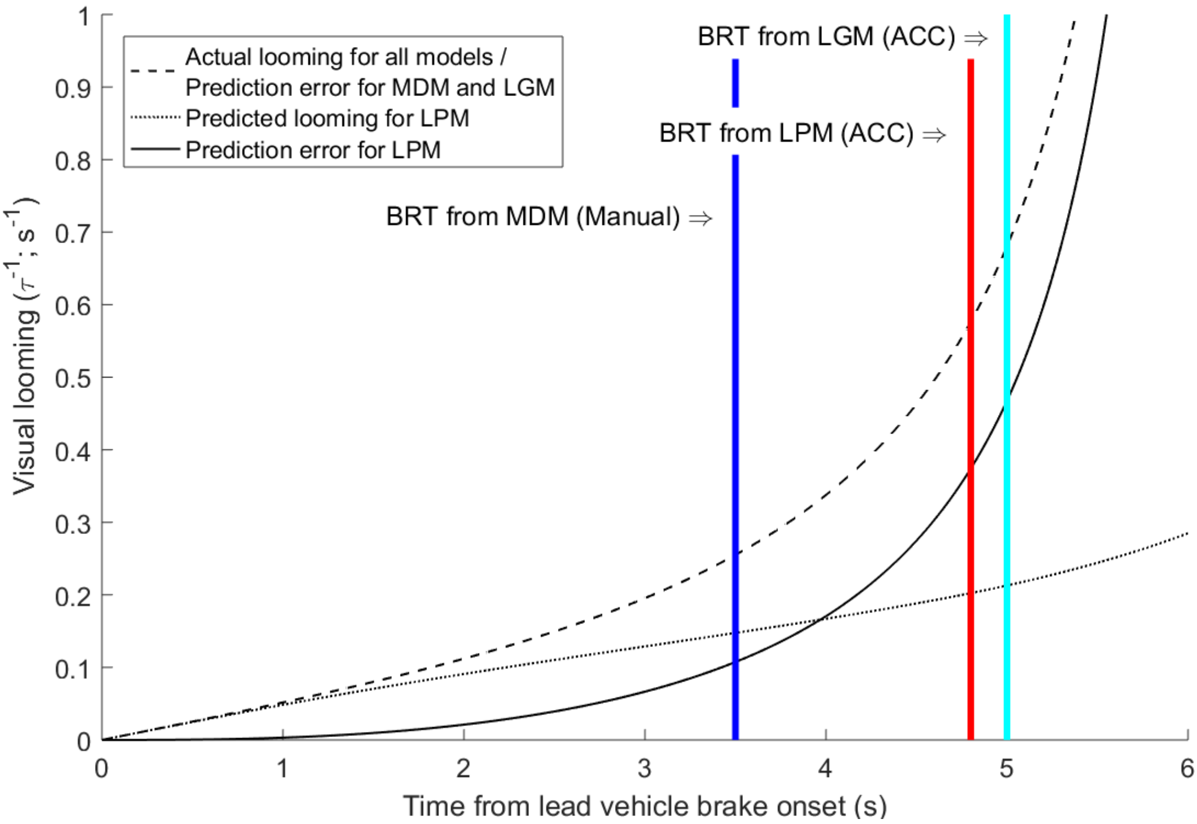

Figure 1: Looming profiles and predicted BRTs during manual driving (*manual driving model*, MDM) and driving with ACC (*looming prediction model*, LPM; *lower gain model*, LGM) in response to lead vehicle deceleration equal to 3.5 m/s^2. Note: BRT was measured as the time that elapsed between the time of lead vehicle deceleration initiation (t = 0) and the time of first braking reaction of the subject vehicle's driver

The upper panel of Figure 2 displays the BRTs predicted by the computational models during manual and driver assistance mode for the simulated scenario, across different lead vehicle deceleration levels. For both driving modes, an increase in lead vehicle deceleration produces a shorter predicted brake reaction time. Furthermore, both the looming prediction model and the lower gain model predict longer BRTs in automated mode compared to the predictions of the manual driving model. For comparison, the upper panel of Figure 2 also shows the predictions of the TTC-based (or looming threshold-based) model by Seppelt and Lee (2015), which assumes a fixed brake response time of 1.5 s after the TTC falls to 4 s (and inverse tau reaches 0.25 s^{-1}). This model predicts very similar BRTs as the models for driver assistance mode – especially the lower gain model – but only makes predictions for ACC, not manual driving.

As shown in the lower panel of Figure 2, the lower gain model predicts a clear interaction effect between lead vehicle deceleration rate and automation mode: the difference in BRT between ACC and manual driving is smaller for increasingly critical lead vehicle decelerations. A similar interaction is discernible for the looming prediction model, but much less markedly so.

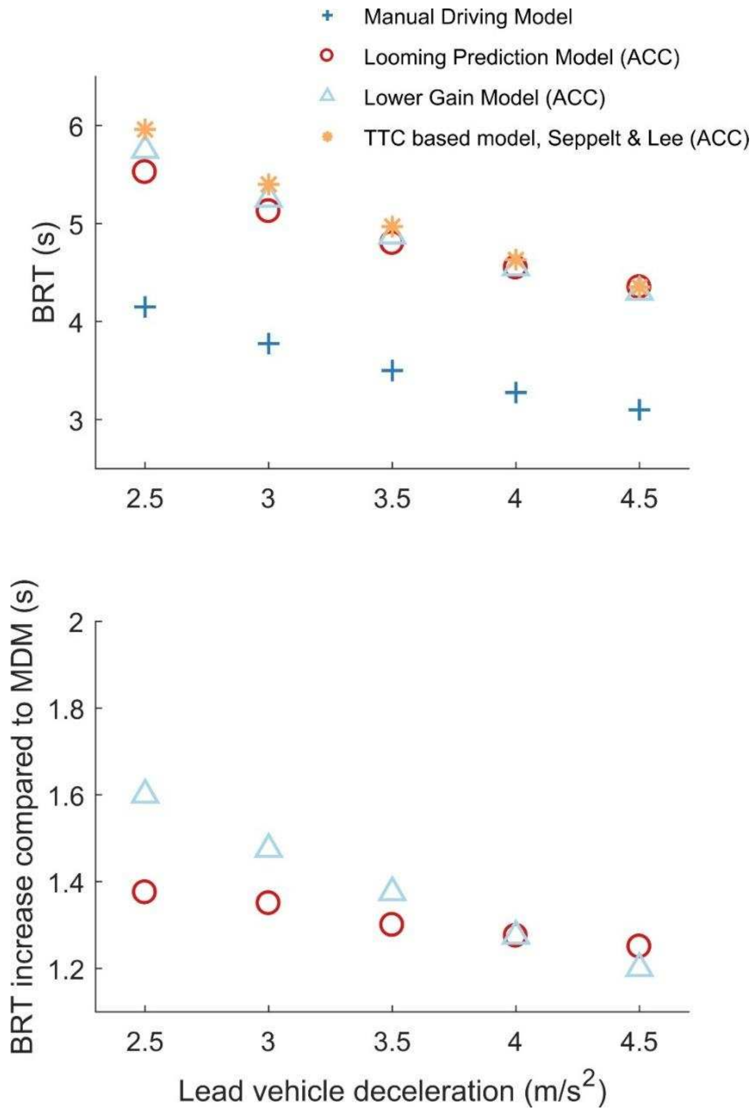

Figure 2: (top) BRTs predicted by the *manual driving model* (MDM) and by three models (*looming prediction model*, *lower gain model* and *TTC-based model*) for driving in driver assistance mode, as a function of lead vehicle deceleration rate. (bottom) Difference in BRTs between models for driving in driver assistance mode (*looming prediction model* and *lower gain model*) and model for driving in manual mode (*manual driving model)* as a function of lead vehicle deceleration rate. Note: BRT was measured as the time that elapsed between the time of lead vehicle deceleration initiation and the time of first braking reaction of the subject vehicle's driver

3. Driving simulator study

This section describes the driving simulator study, carried out to test the following predictions from the computational driver models:

- The manual driving model and the models for driver assistance mode predict that BRTs will be shorter for higher lead vehicle decelerations.
- The models for driver assistance mode predict longer BRTs compared to the manual driving model.
- The lower gain model predicts a clear interaction between automation mode and lead vehicle deceleration level, whereas the looming prediction model does not.

The simulator study also served the purpose of providing data for refitting the models and conduct a more detailed model comparison, which will be described in Chapter 4.

3.1 Materials and methods

3.1.1 Participants

The recruitment of the final 54 participants was conducted via mailing lists, leaflets, and personal advertising (e.g. social media). To take part in the study, the subjects were required to hold a valid driving license, to have driving experience in Sweden for at least three years, to drive at least three times a week, and to not use ACC in their regular car. The last requirement was introduced to avoid the confounding effects of the experience with ACC on the results of the study. Overall, 44 participants had previous experience with CC and 22 participants had previous experience with ACC but no information was collected about previous experience with other ADAS.

During the experiment, five drivers had to be excluded reducing the sample to 49 participants. One participant experienced simulator sickness: the participant needed a longer than usual break after the trial with CC. Although no reason was provided by the participant, the frequent decelerations experienced during the drive might have been the factor causing the simulation sickness (Stoner et al., 2011). Besides, three participants experienced technical issues during the drive, due to scenario programming errors. Finally, the remaining excluded participant did not understand the functional principle of CC during the experiment and its data was therefore not used for the analysis.

The resulting 49 drivers (12 female and 37 male) were aged between 19 and 63 years (M = 41.7; SD = 12.3) and drove about 7.0 times per week (SD = 4.4). Also, they reported to hold a driving license for 23.2 years on average (SD = 12.5) with a life-time mileage of more than 30.000 km for 38 participants and between 3.000 km and 30.000 km for 11 participants.

3.1.2 Apparatus

The study was conducted in the SIM IV moving-base, high-fidelity simulator at VTI premises in Gothenburg (Figure 3; Jansson et al., 2014). The simulator included a mock-up of a Volvo XC60 cabin where the left and right-hand side mirrors were replaced with LCD screens, and a forward screen using front projection technique from nine projectors with resolution of 1280x960 pixels. The overall field of view was about 180 x 50 degrees.

Figure 3: VTI Sim IV driving simulator (Photo by Hejdlösa bilder)

The CC and ACC used in this simulator were simplified versions of the systems available on the market. CC always maintained the ‘set speed’ of 100 km/h when activated and did not take over longitudinal control in reaction to the lead car braking and acceleration. The driver was not able to change the speed, so that the kinematic conditions of braking events could be controlled. ACC maintained a speed of 100 km/h when activated but it also adjusted the speed of the car dynamically to keep a set time headway of 2.5 s to the lead vehicle. Both systems could be activated by pressing a button on the steering wheel and deactivated by pressing the button again, by braking or by using the throttle. Since the participants were not able to change the settings of the systems (speed for CC and speed and time headway for ACC), there was no specific information shown on the main display of the vehicle.

3.1.3 Procedure and experimental design

The study was conducted in October 2017 and took about 1.5 hours for each participant to complete. Before starting, the participants were informed about the purpose (evaluation of driver assistance systems) and the general procedure of the experiment but no details were provided about the ACC failure. After the introduction, the participants gave informed consent to participate.

The participants were then introduced to the simulator and were instructed about the main controls to drive the vehicle (e.g. steering wheel, gearshift, pedals). Additionally, they were provided with customized written manuals for either the CC or ACC before starting the drive with the respective system. Once they completed the study, the participants were requested to fill in a questionnaire, including queries about demographic information (e.g. age), driving experience (e.g. weekly mileage driven) and systems' performance during the study (e.g. ACC failure). Afterwards, they were rewarded with two cinema tickets, of which the monetary value was approximately equivalent to 25 euros. The choice of the cinema tickets was guided by previous driving simulator studies conducted at VTI, where the same compensation was provided to the participants.

The driving part was divided into two drives of about 25 minutes each, the first one dedicated to the use of CC and the second one dedicated to the use of ACC. The choice of a within-subject design was mainly driven by the need to have enough participants for the analysis and the modelling of BRTs. Besides, the order of the drives was not counterbalanced among the participants to ensure that the failure situations experienced with ACC would not affect the driving behavior during the drive with CC (where drivers always had to respond themselves to lead vehicle deceleration). In the first drive, the participants started with a guided simulator training to get familiar with the behavior of the simulator. After that, the participants received a guided training for CC and, then, the driving task with CC started. In the second drive, the participants received a guided training for ACC, followed by the driving task with ACC. Between the drives with CC and ACC the participants left the simulator for a short break and instructions for the second drive.

In both drives, the participants followed a white van on a 2+1 Swedish road. These roads are three-lane highways, consisting of two lanes in one direction, and one lane in the other, alternating every few kilometers and usually separated by a steel-cable barrier. The two-lane segments allow for overtaking without the risk of oncoming vehicles. Driving sections could contain either one or two lanes whose widths were set at 3.25 m (Figure 4). The participants were instructed to stay in the right lane and follow the lead vehicle without overtaking it. Furthermore, participants were instructed to always use the respective driver assistance systems and to reactivate it as soon and as safely as possible, in case of deactivation.

Figure 4: Simulated scenario showing the 2+1 Swedish road

During each drive with CC and ACC, the participants encountered six events with different lead vehicle decelerations (Figure 5): the participants drove for about 2.5 minutes – depending on the travelling speed – between each event. The deceleration of the lead vehicle was triggered on road sections where there was only one lane in the driving direction and physical barrier on the left side, to promote avoidance by braking rather than steering. The presence of a reduction in the number of lanes (from 2 to 1) was always associated to the lead vehicle deceleration but the exact location of the lead vehicle braking within the one-lane section was randomized to prevent participants to anticipate the exact timing of the lead car braking.

The participants were divided in three groups and the lead vehicle deceleration in both drives differed among the groups in the third and sixth braking events. For the remaining events, the lead vehicle deceleration in both drives was the same for all participants. During the ACC drive, failures occurred in the third and sixth braking events: in those situations, the ACC did not react to the lead car braking and the subject vehicle proceeded with speed of 100 km/h unless the driver deactivated the system.

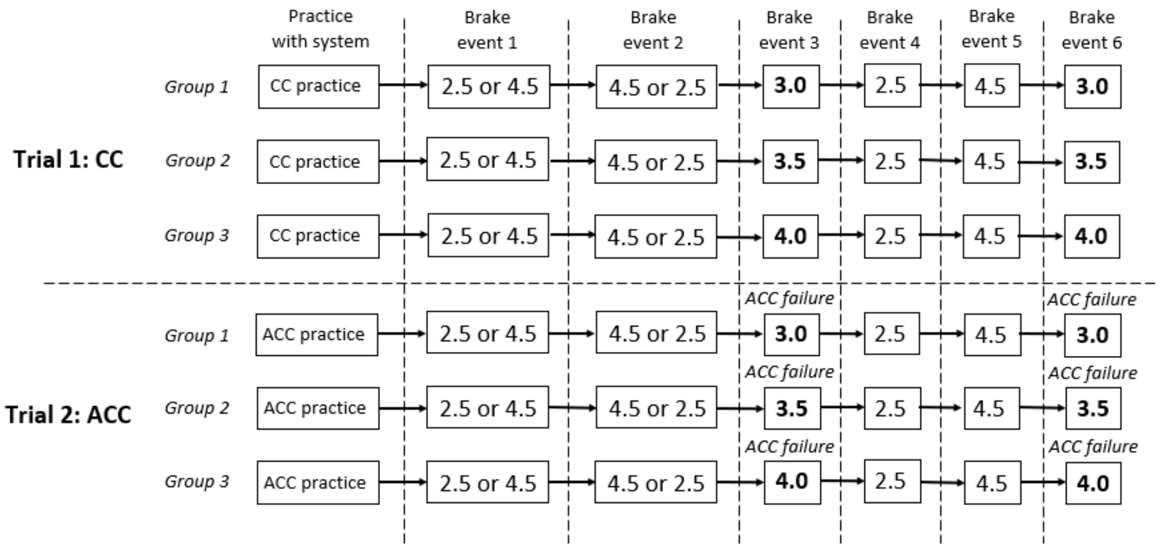

Figure 5: Experimental design. In the figure, the numbers indicate the different levels of lead vehicle decelerations from 2.5 m/s^2 to 4.5 m/s^2. For the first and second events, the levels of decelerations 2.5 m/s^2 and 4.5 m/s^2 were counterbalanced between the participants but all participants experienced both. For the third and sixth events, the participants experienced different lead vehicle decelerations (3.0 m/s^2, 3.5 m/s^2 or 4.0 m/s^2) according to the group they belonged to. Also, for the drive with ACC, the failures of the systems occurred in the third and sixth events.

3.1.5 Data processing

The analyses assessed the BRTs for the six braking events with both systems. However, for ACC driving, the focus was on the failure events since we did not expect drivers to brake when ACC was properly functioning. The data were extracted with MATLAB (version 2016b) and the statistical analyses and plotting were performed with R (version 3.4.3).

3.2 Results

The results report the analysis of BRTs during driving with CC and ACC (section 3.2.1) and the analysis of the subjective data, encompassing the answers to the queries about systems' performance during the driving simulator study (section 3.2.2).

3.2.1 BRTs

Figure 6 shows BRTs as a function of driving mode and kinematic criticality: the BRTs during ACC driving have more variability compared to CC driving.

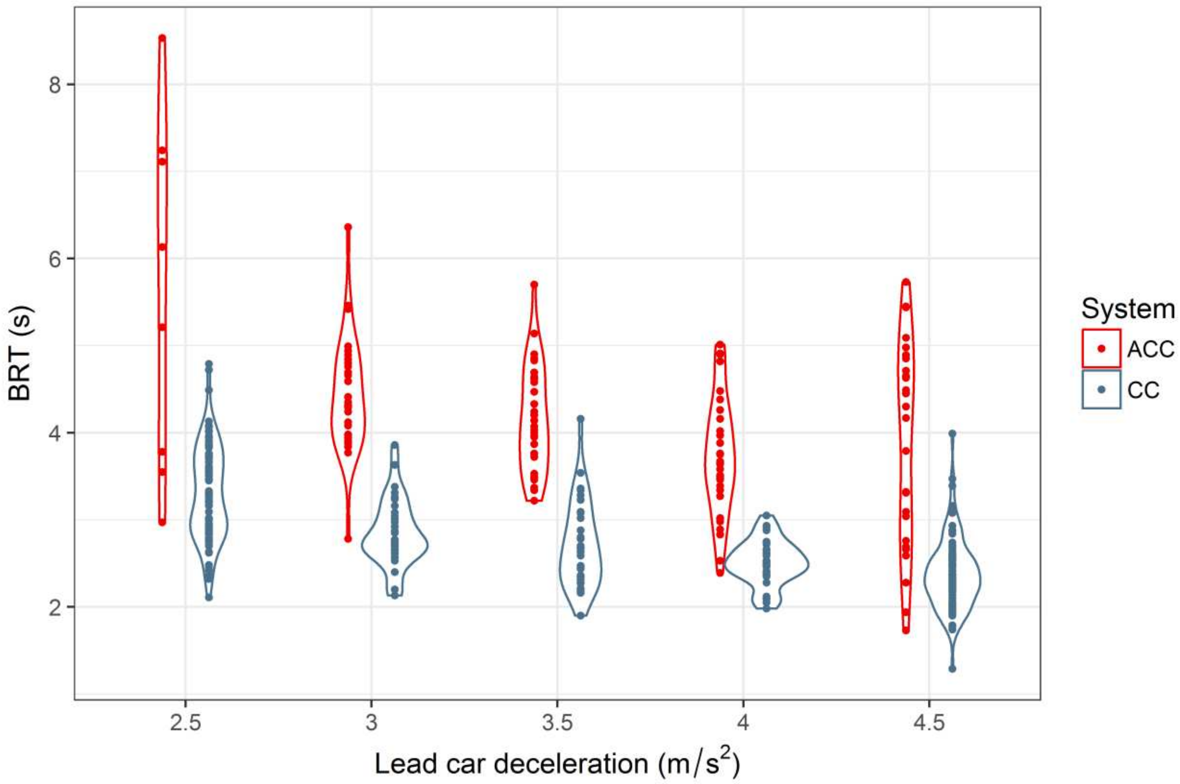

Figure 6. BRTs as a function of driving mode (CC in blue vs. ACC in red) and lead vehicle deceleration. All participants experienced lead vehicle decelerations corresponding to 2.5 m/s² and 4.5 m/s², whereas any given participant only experienced one of the three intermediate deceleration levels (3.0 m/s², 3.5 m/s² and 4.0 m/s²), at which also ACC failures occurred. The ACC worked properly for lead vehicle decelerations of 2.5 m/s² and 4.5 m/s² but nevertheless some drivers braked, and their BRTs are reported in the figure.

Figure 7 reports the four linear regressions models fitted to the data – one for each system-repetition combination – and shows a clear trend for BRTs becoming longer when the kinematic criticality decreases.

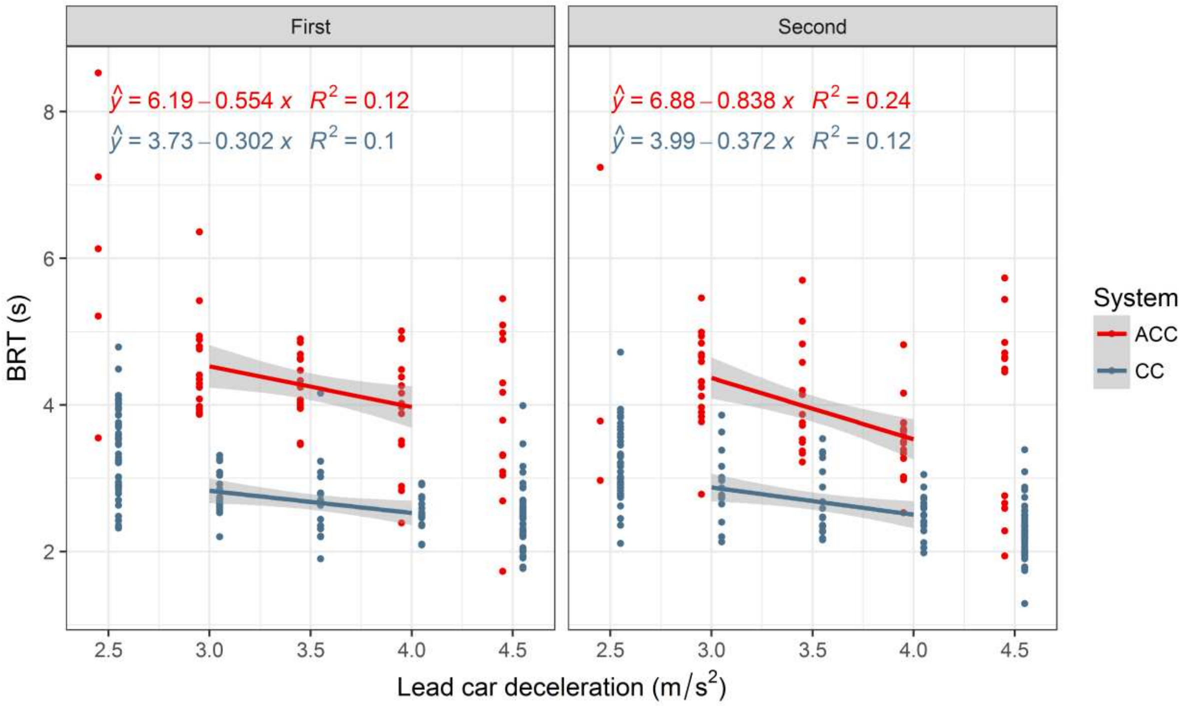

Figure 7. Four linear regression models fitted to the BRTs as a function of system (CC and ACC) and repetition (first vs. second) using the three level of kinematic criticality which were varied between subjects. Points shifted horizontally for readability. Regression line with 95 % CI.

The effect of variations in driving mode and kinematic criticality and the effect of repetition on BRTs were tested with repeated measures ANOVA, using the data from the third and sixth braking events (Figure 8). The kinematic criticality (3.0, 3.5, and 4.0 m/s^2) was a between-subjects factor, and the system (CC or ACC) and repetition (the first and the second failure situation) were within-subjects factors. All significant ($p < .05$) effects are reported.

Situations with lower kinematic criticality had longer BRTs, F(1,46) = 9.58, $p < .01$, ηp2 = 0.29 and polynomial contrasts indicated a linear trend. BRTs were longer when driving with ACC compared to CC, F(1,46) = 329.53, $p < .01$, ηp2 = 0.88. Specifically, the interaction of kinematic criticality and system was not significant, F(2,46) = 1.81, p = .17, providing tentative support for the looming prediction model over the lower gain model; it should be noted however that the observed interaction was nevertheless in the direction predicted by the latter model.

The interaction between repetition and system was significant, $F(1,46) = 5.81$, $p = .02$, $\eta p2 = 0.11$; with ACC, BRTs were longer in the first failure compared to the second one ($p < .01$), but with CC there was no significant difference. This suggests that, after the first failure, drivers already expected that ACC may not function and were more prepared to intervene.

Figure 8 also reports the a priori average BRT predictions of the computational models described in Section 2.2, together with the empirical data from the driving simulator study. The a priori computational models, while reproducing a similar overall pattern of results, do not accurately predict the absolute BRTs from the driving simulator study.

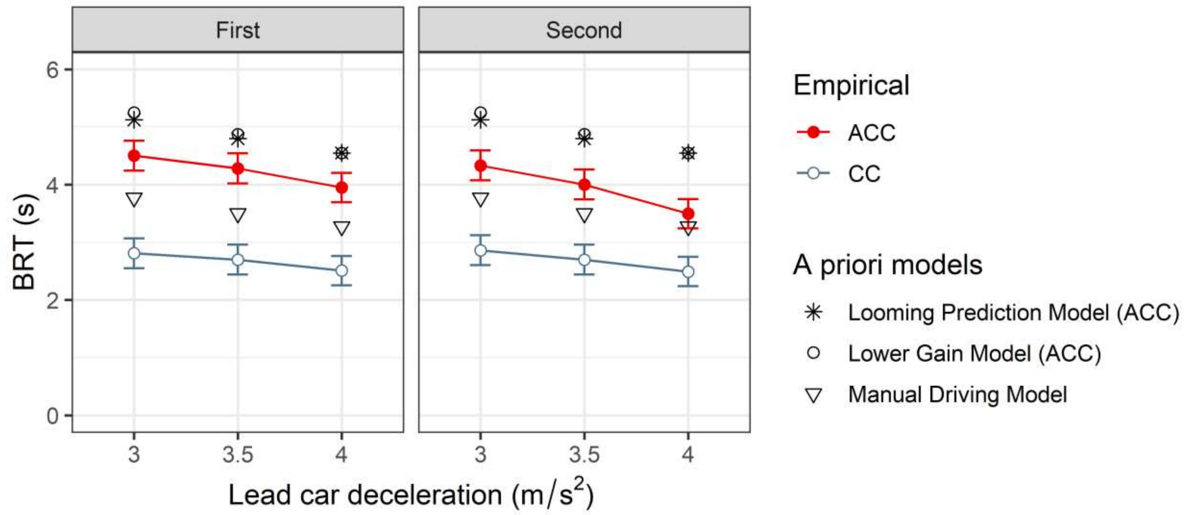

Figure 8. BRTs obtained from the driving simulator study (empirical) and predicted by the a priori computational models (a priori models) as a function of kinematic criticality (lead vehicle deceleration values from 3.0 m/s2 to 4.0 m/s2), system (CC or ACC), and repetition (first vs. second). For empirical data, Least Squares Means with 95% CIs based on the repeated measures ANOVA (see 3.2.) are shown.

3.2.2 Subjective data

In the questionnaire filled in at the end of the driving simulator study, the participants were required to provide an answer to the following query, regarding the performance of ACC: "What was the first thing that alarmed you that there was a failure?" Most of the drivers (27 participants, 55.1% of the sample) realized that a failure occurred because the ACC did not handle the situation as they expected, through appropriate initiation of braking. For example, the participants wrote “I didn't feel or hear the car decelerate, when I experienced it decelerate before or where I would have chosen to start the process of decelerating” or “The distance became shorter and the car didn't decelerate” or “The system tried to brake, but my reaction was that the braking distance was too short.” Besides, 12 participants (24.5% of the sample) recognized the failure because the distance to the lead vehicle decreased more than they would have expected, as stated in these replies: “I was too close to the car in front” or “The car in front of me got closer too quickly” or “I approached the vehicle in front of me too fast.” Finally, the remaining participants did not notice a failure of the system (9 participants, 18,4% of the sample) or identified a system failure different from the one simulated during the experiment (1 participant, 2,0% of the sample).

Overall, the subjective data seem to provide support for the looming prediction model since most of the drivers (55.1% of the sample) had expectations about the ACC deceleration or about the ACC functionality to maintain a minimum distance to the lead vehicle, during the emergency rear-end situations.

4. Fitting and comparison of the computational driver models

As reported in section 3.2.1, the a priori computational models do not accurately predict the absolute BRTs from the driving simulator study. To yield better predictions of BRTs, and to allow a detailed model comparison, the models were fitted to the driving simulator data. First, the manual driving model was fitted to the data from driving with CC. Predictions for the ACC condition could then be directly generated for the looming prediction model, retaining all the parameters from the manual driving model fitted to the CC data. For the lower gain model instead, the k parameter was refitted to the ACC data, while keeping the other parameters fixed as in the manual driving model fitted to the CC data. Since a significant interaction effect between repetition and system was found from the analyses of the driving simulator study, the models were fitted only to the data from the first lead vehicle deceleration event per participant. Also, only the scenarios in the range 3.0 – 4.0 m/s^2 were considered for the fitting given that ACC failures occurred for those lead vehicle decelerations. Table 2 reports the values of the parameters for the models fitted to the driving simulator data. In addition, Figure 9 shows the distribution of BRTs predictions yielded by the three fitted models and the BRTs from the driving simulator study, in the first repetition.

Table 2: Values of the parameters for the models fitted to the driving simulator data. The values in bold are free model parameters while the other values are fixed model parameters

Model	**Values of model parameters**		
	K	m	σ
Manual driving model (CC)	**4.8**	**0.025**	**0.16**
Looming prediction model (ACC)	4.8	0.025	0.16
Lower gain model (ACC)	**1.6**	0.025	0.16

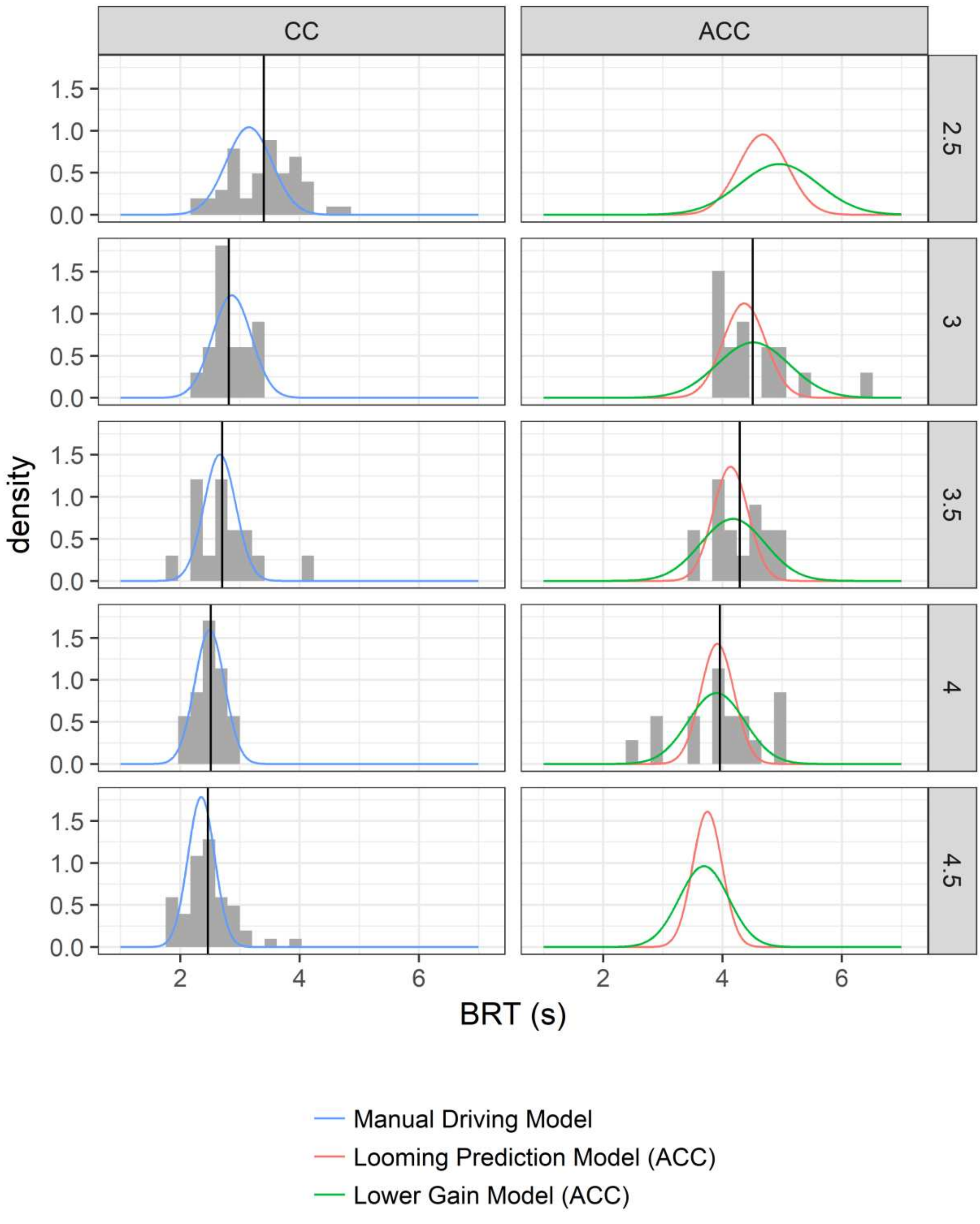

Figure 9: Distribution (histograms) and average values (vertical lines) of BRTs from the driving simulator study and distributions of BRTs predicted by the fitted computational models (curves) as a function of kinematic criticality (deceleration values from 2.5 to 4.5 m/s^2) and system (CC or ACC). For the driving simulator data, only the first three events (the first encounter of each kinematic criticality) were included in the figure. Besides, the distributions of BRTs from the driving simulator study are not reported for deceleration values of 2.5 and 4.5 m/s^2 during driving with ACC, due to the small number of drivers braking.

Overall, it can be observed that: 1) the fitted manual driving model predicts relatively well the BRT distributions during driving with CC, both in terms of average BRT and variability; 2) both the fitted looming prediction model and the lower gain model predict relatively well the average BRTs during driving with ACC, but both models, and especially the looming prediction model, predict somewhat lower BRT variabilities than observed. From a comparison of the two models by the Akaike Information Criterion (AIC; Akaike, 1973), the lower gain model had a notable lower AIC (260.39) than the looming prediction model (266.40). Overall, the lower gain model appears to predict better the increased variability of BRTs with ACC, and it had also a lower AIC.; however, the lower gain model introduces an additional free parameter, compared to the looming prediction model, and predicts a clear interaction effect between kinematic criticality and automation mode, which was not confirmed by the driving simulator data.

5. Discussion

This paper presented novel kinematics-dependent computational driver models to predict BRTs in rear-end critical scenarios during driving manually (manual driving model) and with ACC (looming prediction model and lower gain model). The computational models were developed as instances of the model described by Svärd et al. (2017) and assumed that drivers respond to visual looming, reflecting the kinematics of the situation. Compared to previous models based on visual looming (Flach et al., 2004; Markkula, 2014; Markkula et al., 2016; Markkula & Engström, 2017; Engström et al., 2017; Venkatraman et al., 2016), the computational models described in this paper assume that, in emergency rear-end situations, drivers react to unexpected looming rather than to looming per se (Engström et al., 2018). Furthermore, our computational models broaden previous work by providing a description of drivers' responses not only during manual driving, but also during driving with ACC when the latter fails.

The predictions of the computational models yielded shorter BRTs with increase of kinematic criticality for all models and a delay in BRTs during driving with ACC compared to driving manually. In the models, this delay originated from a slower accumulation of looming prediction error either due to drivers' expectations of ACC braking (looming prediction model), in line with the framework of predictive processing (e.g., Clark, 2013; Clark, 2016; Friston et al., 2010; Engström et al., 2018), or due to lower arousal (lower gain model) caused by monitoring of the ACC system, inducing passive fatigue (Desmond & Hancock, 2001; Greenlee et al., 2018; Saxby et al., 2013; see also Markkula and Engström, 2017).

A driving simulator study was conducted to test the predictions of the computational driver models: 49 participants drove with CC and ACC and experienced six critical events where the lead vehicle braked with different levels of decelerations. In two of the six events, the ACC failed and, therefore, the drivers were expected to take back control from the system. The results of the driving simulator study confirmed the predictions of the computational driver models:

- The BRTs significantly decrease with higher levels of kinematic criticality, both during driving with CC and ACC. This outcome is in line with previous research (Markkula, 2014; Markkula et al., 2016; Markkula & Engström, 2017; Engström et al., 2017; Venkatraman et al., 2016) but shows for the first time this phenomenon in silent failures of automation.
- The BRTs are significantly longer during driving with ACC compared to driving with CC. However, the a priori models' BRTs predictions were longer than the ones observed in the driving simulator study, with this difference ranging between 0.7 and 0.9 seconds. This difference could possibly be explained by the fact that the previous experiments used to parameterize the manual driving model (Engström et al., 2010; Ljung Aust et al., 2012; Markkula et al., 2013; Markkula et al., 2016; Nilsson et al., 2018) had different driving conditions. Most notably, these past studies only considered BRTs for unexpected lead vehicle events, whereas the present driving simulator study had repeated scenario exposures, for which response times are known to be reduced (Lee et al., 2002; Ljung Aust et al., 2013). Also, in past studies, the critical scenario was different (lead vehicle braking after cutting in), the manual driving was performed without CC, and the considered lead vehicle decelerations were also higher compared to the current driving simulator study.

The subjective data collected after the rides in the driving simulator suggest that most of the drivers reacted, during the emergency rear-end situations, due to a mismatch between the expected and the perceived visual cues, when the silent failure of ACC occurred: the drivers expected the ACC to brake and/or maintain a constant time headway (referred as 'distance' by the participants) to the lead vehicle but the visual cues perceived from the environment revealed to the drivers that "The distance became shorter and the car didn't decelerate." This outcome might provide support for the looming prediction model since the drivers seemed to embody a generative model of ACC working principle, although probably still a basic one considered the short experience in driving with the system. Besides, it underlines the importance of appropriate drivers' prediction/expectation about the actions (e.g. braking or steering) undertaken by automated driving systems or driving automation systems (Engström et al., 2018; Victor et al., 2018).

The models were directly fitted to the data from the driving simulator study and were found to capture relatively well the observed BRT distributions. According to the AIC model comparison, the lower gain model was preferable to the looming prediction model, seemingly mainly due to the latter model predicting too low BRT variabilities. However, this should not be taken as strong evidence that the underlying cause for the BRT delay in ACC driving was reduced arousal in this study. Driver arousal was not experimentally measured during the driving simulator study, and the re-fitting of the gain parameter does introduce additional model flexibility. In comparison, arguably a more striking finding was that the looming prediction model was able to predict the average BRTs directly from the manual driving model fitted to the CC data, without any re-fitting of parameters. If nothing else, this property of the looming prediction model may be considered an applied advantage. It should be noted that, in our tests, the looming prediction model was also potentially disadvantaged to some extent by the assumption that the driver has a perfect generative model of the looming profile generated by ACC. Indeed, variability in drivers' looming prediction accuracy could help explain the larger BRT variability in the observed data, compared to the looming prediction model's BRTs. As mentioned, the subjective responses from the participants also aligned well with the looming prediction model. It is also worth noting that – although we described two different models, testing distinct explanatory mechanisms – the two models are not mutually exclusive and may be combined in future studies.

Overall, the present study provided new insights into driver braking reactions in rear-end critical situations originated by automation failures. The key novel contribution of the present paper is the proposal of two computational driver models, parametrized based on driving simulator data, which were both found to be capable of accounting for the delay in drivers' responses to silent ACC failures, compared to driving with CC. These models can then be applied in computer simulations aiming to assess the safety benefits of active safety systems or automated driving (Bärgman et al., 2017; Kusano & Gabler, 2012; McLaughin et al., 2008).

The current study has some limitations. Due to the experimental settings and repeated braking events always occurring at the one-lane section of the road, the participants may have had increased expectancy for lead vehicle braking on these road sections. In addition, all the participants had experienced the CC drive with critical braking events before ACC failures, likely priming the drivers for such events. Due to these limitations, the models might underestimate the delay in response during driving with ACC compared to driving with CC. Besides, during the driving simulator study, the participants were prevented from avoiding the lead vehicle through steering, by the physical barrier on the left side. Therefore, the models presented in this paper consider only braking – and not steering – as possible drivers' avoidance maneuver to the lead vehicle braking. Also, the exposure to driving with ACC in the driving simulator was very brief before experiencing the silent failure of the system: such a short time might have not been sufficient to induce a decrease of arousal in the participants. Hence, additional studies – not least naturalistic driving studies – are needed to further test the lower gain model, as well as the looming prediction model, in situations where drivers are exposed to a failure after long-term use of the system. Furthermore, the models assessing BRTs to rear-end critical scenarios during driver assistance mode are solely valid for situations in which there is a silent failure of the system. Future work should address how drivers would react in the same scenario when a warning (e.g. auditory HMI warning) is provided, to inform the drivers about a performance-relevant system failure. Finally, the models assessing BRTs to rear-end critical scenarios during driver assistance mode did not include kinesthetic cues (e.g. ACC deceleration). Morando et al. (2016) and Fancher et al. (1998) showed that drivers perceive the longitudinal deceleration of ACC in emergency rear-end situations as a cue to direct their gaze towards the forward roadway. Future models describing BRTs in unexpected emergency rear-end situations – originated by functional limitations of ADS (level 3) or driving automation systems (level 1 and level 2) – should incorporate kinesthetic cues, especially in situations where drivers are not looking ahead and might miss visual cues associated to the lead vehicle deceleration.

Key points

- Three computational driver models were described and applied in simulations to predict BRTs in rear-end critical scenarios, induced by different levels of lead vehicle deceleration: one manual driving model to predict BRTs during manual driving (or during driving with CC) and one looming prediction model and one lower gain model to predict BRTs during driving with ACC. The looming prediction model assumes that drivers embody a generative model of ACC while the lower gain model assumes that drivers' arousal decreases due to monitoring of the automated system.

- A driving simulator study was conducted with 49 participants to test the predictions of BRTs issued by the three computational driver models. The study confirmed the predictions of the models: BRTs were significantly shorter with an increase in kinematic criticality, both during driving with CC and ACC and BRTs were significantly delayed when driving with ACC compared to driving with CC. However, the predicted BRTs were longer than the ones observed in the study and, for this reason, a fitting of the models to the data from the driving simulator study was performed.
- Both the fitted looming prediction model and the lower gain model predicted well the BRTs obtained from the driving simulator study in the chosen range of lead vehicle decelerations. Although the lower gain model performs better based on the Akaike Information Criterion (AIC), the looming prediction model has the advantage of being able to predict the average BRTs, directly using parameters of the model fitted to the CC driving data.
- The models resulting from this study can have application in computer simulations aiming to assess the safety benefits of active safety systems or automated driving.

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