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1 How do drivers respond to silent automation failures? Driving 2 simulator study and comparison of computational driver 3 braking models

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18 Précis

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

23

24 Running head

25 Drivers response to automation failures

26 Abstract

27 Objective

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

31

32 Background

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

35

36 Method

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

41

42 Results

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

48

49 Conclusion

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

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55 Application

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

58 **Keywords**

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

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80 1. Introduction

81 Human limitations are widely recognized as a main contributing factor to road crashes
82 (Hendricks et al., 2001; Treat et al., 1979) and the introduction of automated driving is expected
83 to address this issue by automating the driving task (Victor et al., 2017). The degrees of
84 automation for on-road vehicles are classified by the Society of Automotive Engineers (SAE,
85 2018) into different levels, from manual driving up to full driving automation. At the highest
86 levels (4-5), the automated driving system (ADS) should perform the entire dynamic driving
87 task (DDT), without any expectation that a user will respond to a request to intervene. However,
88 at lower levels, the driver is either expected to be receptive to ADS' request to intervene (level
89 3) or to supervise the driving automation system¹ (level 1 and level 2).

90 Existing research has warned about possible human factors issues associated to the supervisory
91 role of the driver, including among others skill degradation (Skottke et al., 2014), complacency
92 (Payre et al., 2016) and negative behavioral adaptations (Jamson et al., 2013; Reimer et al.,
93 2016). Given that automated vehicles may fail (Dikmen & Burns, 2016), a relevant question is
94 how drivers will react in those situations. Many previous studies have investigated driver
95 response to takeover requests from the automated vehicle (Gold et al., 2018) and to a lesser
96 extent also driver responses to *silent failures*, where the automation fails without alerting the
97 driver (Blommer et al., 2017; Strand et al., 2012; Young & Stanton, 2007).

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

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)

- 106 1. Present three computational driver models predicting full probability distributions for
107 BRTs in lead vehicle braking scenarios, across different kinematic conditions, both
108 during driving with Cruise Control (CC) and driving with Adaptive Cruise Control
109 (ACC), when the latter silently fails.
- 110 2. Show the results from a driving simulator study conducted to test the predictions of the
111 computational driver models.
- 112 3. Carry out a detailed comparison of the three computational driver models, after fitting
113 them to the driving simulator data.

114

115 2. Models of driver response in manual and automated mode

116 2.1 Models' descriptions

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

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

132

$$133 \tau = \frac{\theta}{\dot{\theta}} \quad (1)$$

134

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

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

151

$$152 \quad \frac{dA}{dt} = k\varepsilon(t) - m + v(t) \quad (2)$$

153

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

158

$$159 \quad \varepsilon(t) = \tau_a^{-1}(t) - \tau_p^{-1}(t) \quad (3)$$

160

161 where τ_a^{-1} refers to the actual looming (inverse tau) signal and τ_p^{-1} to the predicted looming.
162 The parameter k in Equation 2 can be interpreted as the gain determining the impact of the

163 prediction error on the accumulator while m can be interpreted as the sum of all non-looming
164 evidence for and against the need of braking (Svärd et al., 2017; Markkula, 2014).

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

- 169 1. *Looming prediction model*: in this model, it is assumed that the driver continuously
170 predicts the looming that would arise from a properly functioning ACC, in response to
171 a decelerating lead vehicle, and what is being accumulated in the braking decision
172 process are deviations from this prediction. For simplicity, the predictions are here
173 computed assuming that the driver has a perfect mental representation of the ACC
174 working principle, that is, the driver embodies a perfect *generative model* (Friston et al.,
175 2010) of how looming cues are generated by the ACC.
- 176 2. *Lower gain model*: in this model, it is assumed that a decrease in driver *arousal* occurs
177 due to the monitoring of the ACC, sometimes referred to in terms of *passive fatigue*
178 (Desmond & Hancock, 2001; Greenlee et al., 2018; Saxby et al., 2013). It has been
179 shown that empirically observed effects on response times of increases and decreases in
180 arousal can be well accounted for by increases and decreases in the accumulation gain
181 k in evidence accumulation models (Jepma et al., 2008; Markkula & Engström, 2017;
182 Ratcliff & Van Dongen, 2011).

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

184

185 2.2. A priori model predictions of BRTs

186 We applied the computational driver models in simulations to make initial predictions about
187 the brake reaction times (BRTs) in rear-end conflicts, during driving with CC – henceforward
188 referred as manual mode – and ACC – henceforth referred as driver assistance mode. The
189 simulations aimed to reproduce a typical highway driving scenario, and the same scenario was
190 also used in the driving simulator study described later. Each simulation started with the
191 modelled driver driving either manually or with engaged ACC, at a speed of 100 km/h and
192 keeping a time headway to the lead vehicle of 2.5 seconds. The lead vehicle, initially travelling
193 at 100 km/h, applied a constant deceleration which was varied, between simulations, in the 2.5

194 - 4.5 m/s² range. During driving with engaged ACC, the system had a silent failure when the
 195 lead vehicle started to decelerate.

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

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

Study	Number of participants	SV type	SV instructed initial	LV initial speed [km/h]	Initial THW [s]	LV deceleration [g]	Observed average BRT [s]
-------	------------------------	---------	-----------------------	-------------------------	-----------------	---------------------	--------------------------

			speed [km/h]				
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

221

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

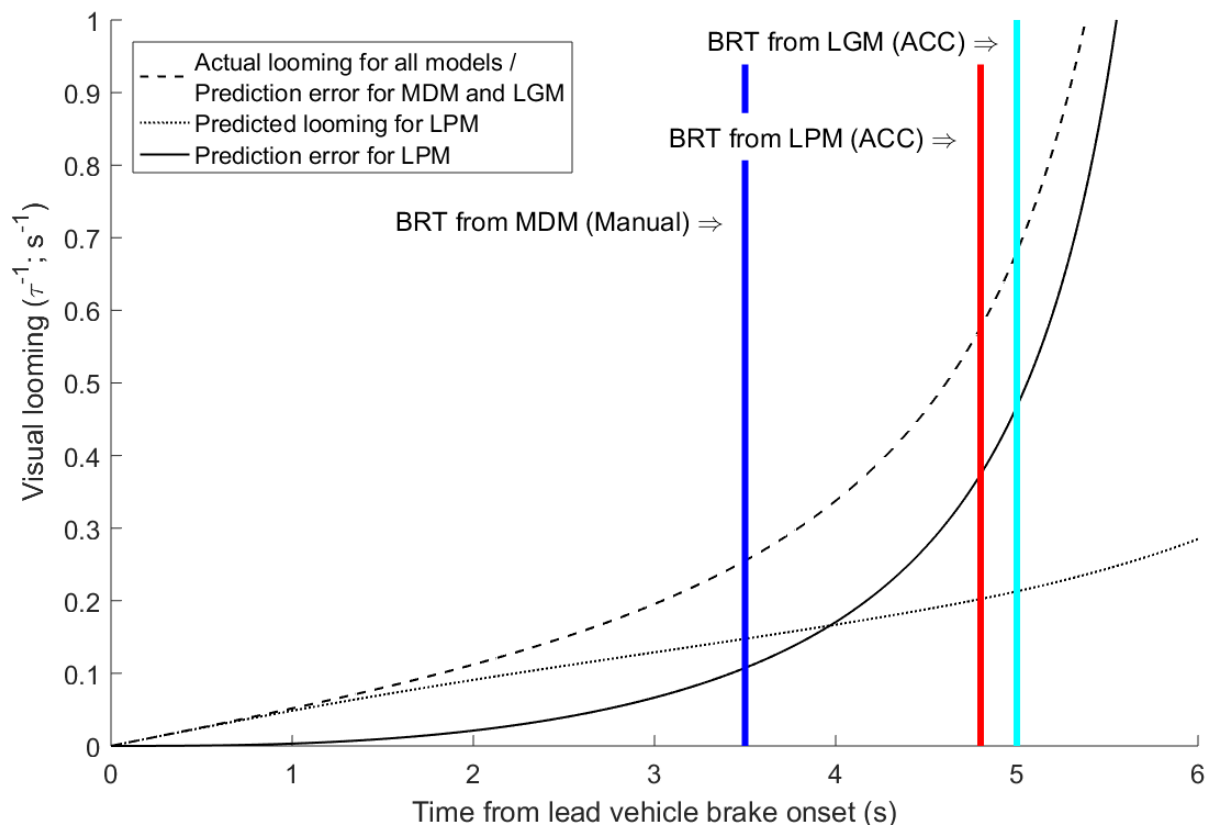
232 In the *manual driving model*, the driver does not expect any initial looming ($\tau_p^{-1} = 0$) and,
233 therefore, the looming prediction error equals the actual looming (dashed line in Figure 1) and
234 increases sharply when the lead vehicle decelerates. The corresponding predicted drivers'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

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

239 In the *looming prediction model*, the values of the model parameters were the same as in the
240 manual driving model ($k = 2.7$, $m = 0$ and $\sigma = 0$). However, while $\tau_p^{-1} = 0$ (no expected
241 looming) in the manual driving model, in the looming prediction model, τ_p^{-1} was the looming
242 that would have been generated in the scenario, had the ACC braked (dotted line in Figure 1).
243 This model thus sees a smaller looming prediction error (solid line in Figure 1) than the manual
244 driving model, and consequently the driver reacts later (red vertical line in Figure 1).

245 The *lower gain model* assumes a change in gain k . Here, $k = 1.1$ was chosen to obtain BRTs
246 roughly comparable to those of the looming prediction model. The remaining parameters ($m =$
247 0 and $\sigma = 0$) and the calculation of the looming prediction error (Equation 3) were the same as
248 in the manual driving model, that is the driver did not expect any initial looming ($\tau_p^{-1} = 0$).
249 However, due to the lower gain, also in this model the driver reacts later (magenta vertical line
250 in Figure 1).

251



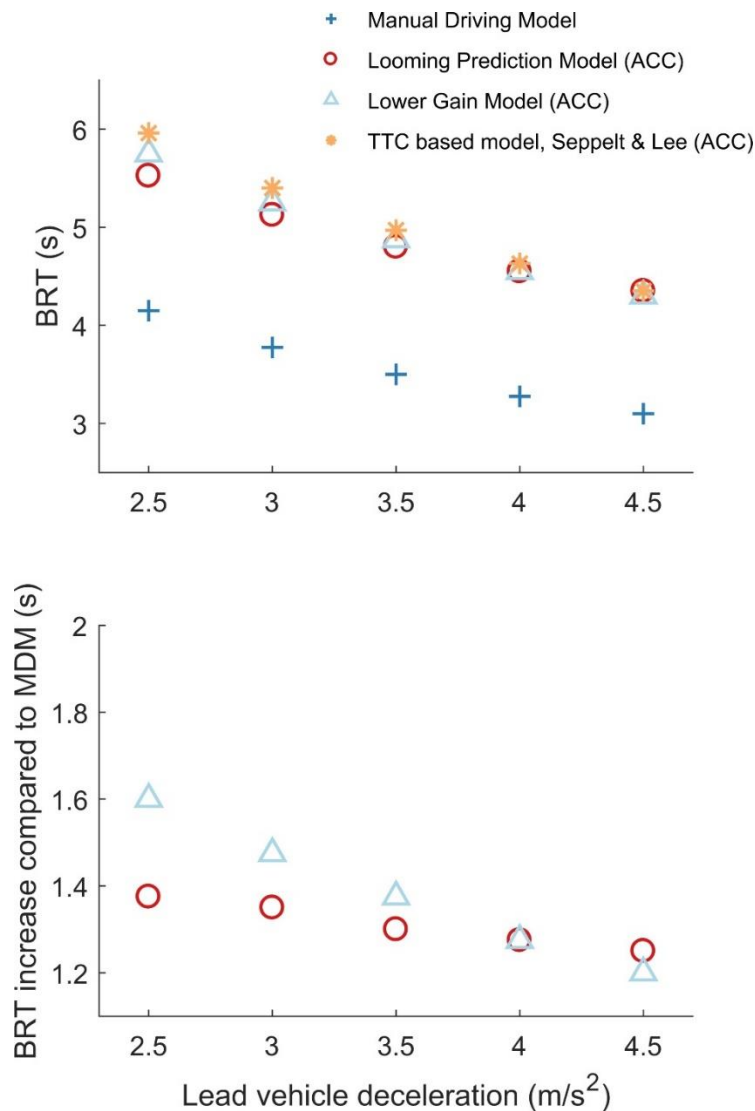
252

253 **Figure 1: Looming profiles and predicted BRTs during manual driving (*manual driving model, MDM*)**
254 **and driving with ACC (*looming prediction model, LPM; lower gain model, LGM*) in response to lead**
255 **vehicle deceleration equal to 3.5 m/s². Note: BRT was measured as the time that elapsed between**
256 **the time of lead vehicle deceleration initiation (t = 0) and the time of first braking reaction of the**
257 **subject vehicle's driver**

258

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

270 As shown in the lower panel of Figure 2, the lower gain model predicts a clear interaction effect
271 between lead vehicle deceleration rate and automation mode: the difference in BRT between
272 ACC and manual driving is smaller for increasingly critical lead vehicle decelerations. A
273 similar interaction is discernible for the looming prediction model, but much less markedly so.
274



275
276
277 **Figure 2: (top) BRTs predicted by the *manual driving model* (MDM) and by three models (*looming***
278 ***prediction model, lower gain model and TTC-based model*) for driving in driver assistance mode, as**
279 **a function of lead vehicle deceleration rate. (bottom) Difference in BRTs between models for driving**
280 **in driver assistance mode (*looming prediction model and lower gain model*) and model for driving in**
281 **manual mode (*manual driving model*) as a function of lead vehicle deceleration rate. Note: BRT was**

282 measured as the time that elapsed between the time of lead vehicle deceleration initiation and the
283 time of first braking reaction of the subject vehicle's driver

284

285 3. Driving simulator study

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

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

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

296

297 3.1 Materials and methods

298 3.1.1 Participants

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

307 During the experiment, five drivers had to be excluded reducing the sample to 49 participants.
308 One participant experienced simulator sickness: the participant needed a longer than usual
309 break after the trial with CC. Although no reason was provided by the participant, the frequent

310 decelerations experienced during the drive might have been the factor causing the simulation
311 sickness (Stoner et al., 2011). Besides, three participants experienced technical issues during
312 the drive, due to scenario programming errors. Finally, the remaining excluded participant did
313 not understand the functional principle of CC during the experiment and its data was therefore
314 not used for the analysis.

315 The resulting 49 drivers (12 female and 37 male) were aged between 19 and 63 years ($M =$
316 41.7 ; $SD = 12.3$) and drove about 7.0 times per week ($SD = 4.4$). Also, they reported to hold a
317 driving license for 23.2 years on average ($SD = 12.5$) with a life-time mileage of more than
318 30.000 km for 38 participants and between 3.000 km and 30.000 km for 11 participants.

319

320 3.1.2 Apparatus

321 The study was conducted in the SIM IV moving-base, high-fidelity simulator at VTI premises
322 in Gothenburg (Figure 3; Jansson et al., 2014). The simulator included a mock-up of a Volvo
323 XC60 cabin where the left and right-hand side mirrors were replaced with LCD screens, and a
324 forward screen using front projection technique from nine projectors with resolution of
325 1280x960 pixels. The overall field of view was about 180 x 50 degrees.

326



327

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

329

330 The CC and ACC used in this simulator were simplified versions of the systems available on
331 the market. CC always maintained the ‘set speed’ of 100 km/h when activated and did not take

332 over longitudinal control in reaction to the lead car braking and acceleration. The driver was
333 not able to change the speed, so that the kinematic conditions of braking events could be
334 controlled. ACC maintained a speed of 100 km/h when activated but it also adjusted the speed
335 of the car dynamically to keep a set time headway of 2.5 s to the lead vehicle. Both systems
336 could be activated by pressing a button on the steering wheel and deactivated by pressing the
337 button again, by braking or by using the throttle. Since the participants were not able to change
338 the settings of the systems (speed for CC and speed and time headway for ACC), there was no
339 specific information shown on the main display of the vehicle.

340

341 3.1.3 Procedure and experimental design

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

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

357 The driving part was divided into two drives of about 25 minutes each, the first one dedicated
358 to the use of CC and the second one dedicated to the use of ACC. The choice of a within-subject
359 design was mainly driven by the need to have enough participants for the analysis and the
360 modelling of BRTs. Besides, the order of the drives was not counterbalanced among the
361 participants to ensure that the failure situations experienced with ACC would not affect the
362 driving behavior during the drive with CC (where drivers always had to respond themselves to

363 lead vehicle deceleration). In the first drive, the participants started with a guided simulator
364 training to get familiar with the behavior of the simulator. After that, the participants received
365 a guided training for CC and, then, the driving task with CC started. In the second drive, the
366 participants received a guided training for ACC, followed by the driving task with ACC.
367 Between the drives with CC and ACC the participants left the simulator for a short break and
368 instructions for the second drive.

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

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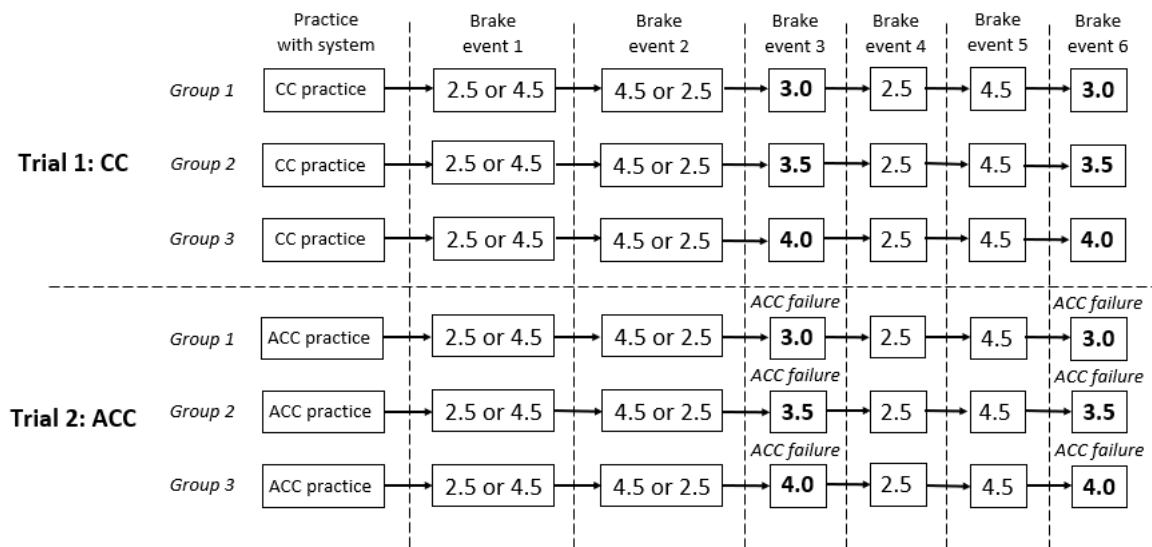
379 **Figure 4: Simulated scenario showing the 2+1 Swedish road**

380

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

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

395



396

397 **Figure 5: Experimental design.** In the figure, the numbers indicate the different levels of lead vehicle
 398 decelerations from 2.5 m/s² to 4.5 m/s². For the first and second events, the levels of decelerations
 399 2.5 m/s² and 4.5 m/s² were counterbalanced between the participants but all participants
 400 experienced both. For the third and sixth events, the participants experienced different lead vehicle
 401 decelerations (3.0 m/s², 3.5 m/s² or 4.0 m/s²) according to the group they belonged to. Also, for the
 402 drive with ACC, the failures of the systems occurred in the third and sixth events.

403

404 3.1.5 Data processing

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

409

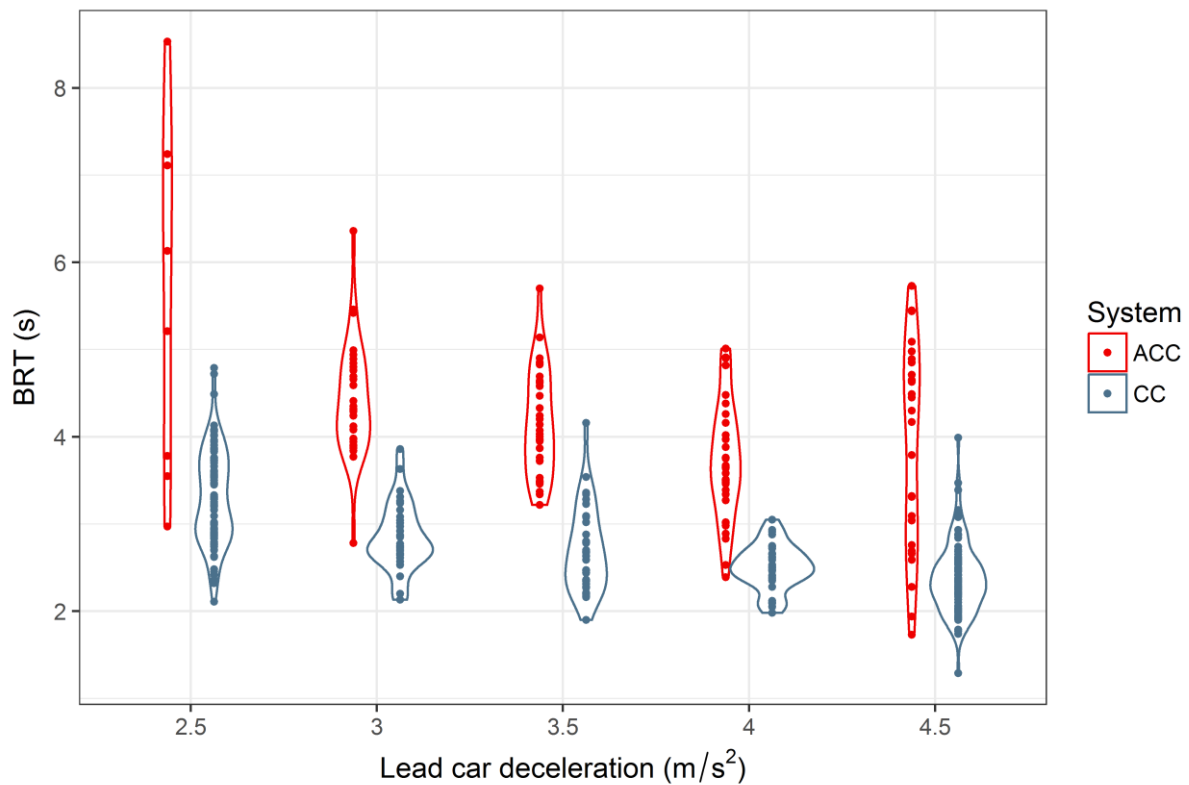
410 3.2 Results

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

414 3.2.1 BRTs

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

417



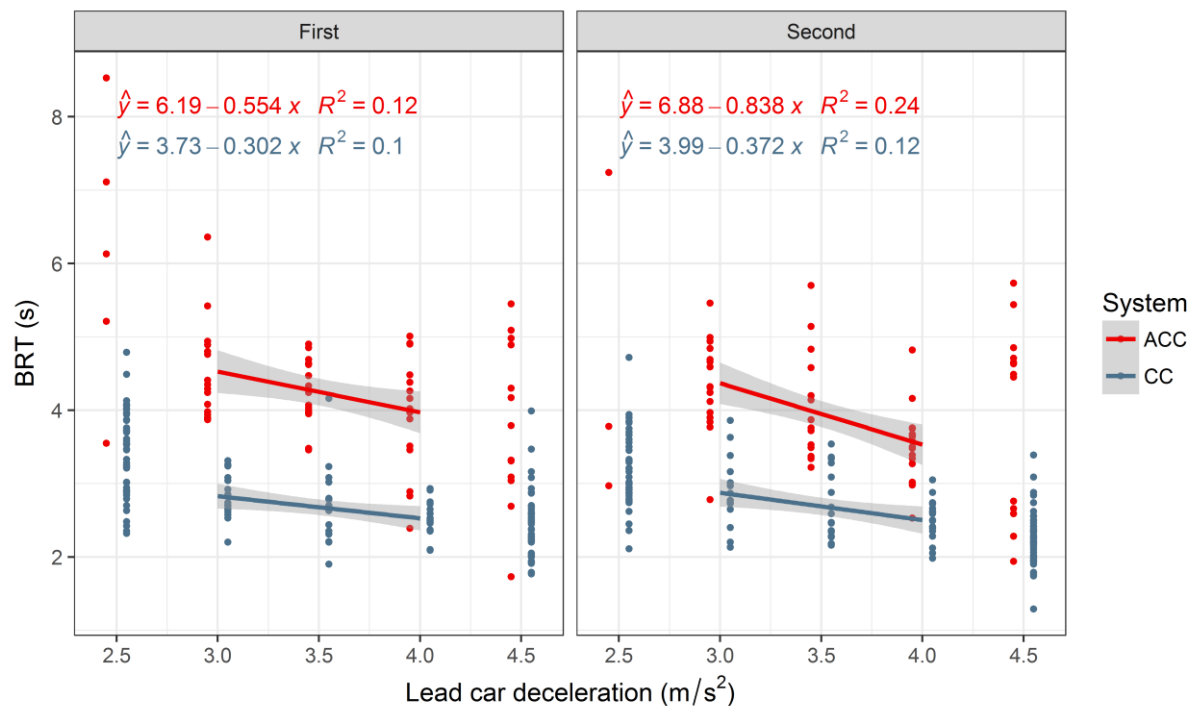
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419 **Figure 6. BRTs as a function of driving mode (CC in blue vs. ACC in red) and lead vehicle deceleration.**
420 **All participants experienced lead vehicle decelerations corresponding to 2.5 m/s² and 4.5 m/s²,**
421 **whereas any given participant only experienced one of the three intermediate deceleration levels**
422 **(3.0 m/s², 3.5 m/s² and 4.0 m/s²), at which also ACC failures occurred. The ACC worked properly for**
423 **lead vehicle decelerations of 2.5 m/s² and 4.5 m/s² but nevertheless some drivers braked, and their**
424 **BRTs are reported in the figure.**

425

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

429



430

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

434

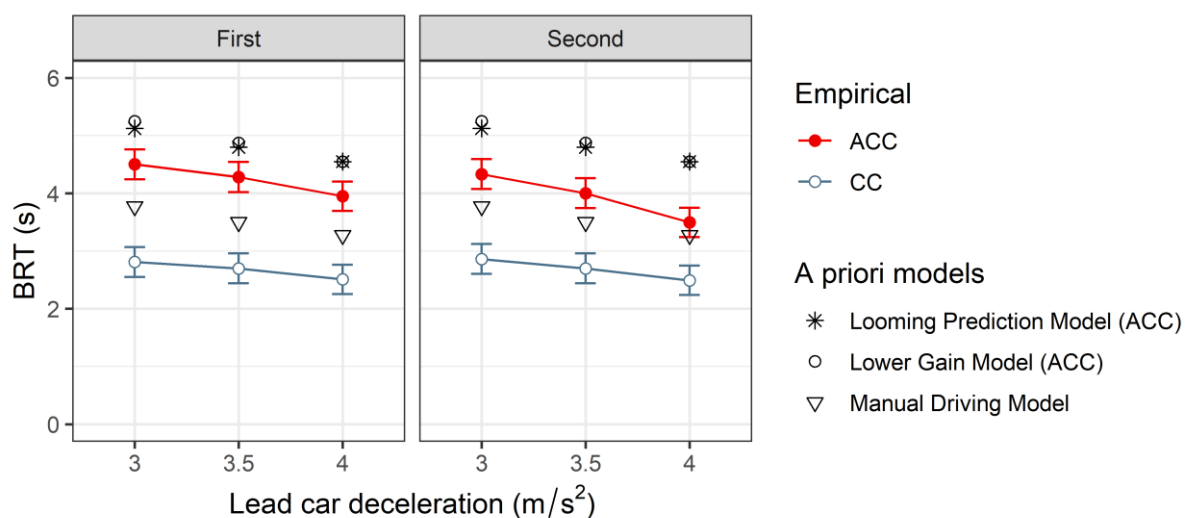
435 The effect of variations in driving mode and kinematic criticality and the effect of repetition on
 436 BRTs were tested with repeated measures ANOVA, using the data from the third and sixth
 437 braking events (Figure 8). The kinematic criticality (3.0, 3.5, and 4.0 m/s²) was a between-
 438 subjects factor, and the system (CC or ACC) and repetition (the first and the second failure
 439 situation) were within-subjects factors. All significant ($p < .05$) effects are reported.

440 Situations with lower kinematic criticality had longer BRTs, $F(1,46) = 9.58$, $p < .01$, $\eta^2 = 0.29$
 441 and polynomial contrasts indicated a linear trend. BRTs were longer when driving with ACC
 442 compared to CC, $F(1,46) = 329.53$, $p < .01$, $\eta^2 = 0.88$. Specifically, the interaction of
 443 kinematic criticality and system was not significant, $F(2,46) = 1.81$, $p = .17$, providing tentative
 444 support for the looming prediction model over the lower gain model; it should be noted however
 445 that the observed interaction was nevertheless in the direction predicted by the latter model.
 446 The interaction between repetition and system was significant, $F(1,46) = 5.81$, $p = .02$, $\eta^2 =$
 447 0.11 ; with ACC, BRTs were longer in the first failure compared to the second one ($p < .01$),

448 but with CC there was no significant difference. This suggests that, after the first failure, drivers
449 already expected that ACC may not function and were more prepared to intervene.

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

454



455

456 **Figure 8. BRTs obtained from the driving simulator study (empirical) and predicted by the a priori**
457 **computational models (a priori models) as a function of kinematic criticality (lead vehicle**
458 **deceleration values from 3.0 m/s² to 4.0 m/s²), system (CC or ACC), and repetition (first vs. second).**
459 **For empirical data, Least Squares Means with 95% CIs based on the repeated measures ANOVA (see**
460 **3.2.) are shown.**

461

462 3.2.2 Subjective data

463 In the questionnaire filled in at the end of the driving simulator study, the participants were
464 required to provide an answer to the following query, regarding the performance of ACC:
465 “What was the first thing that alarmed you that there was a failure?” Most of the drivers (27
466 participants, 55.1% of the sample) realized that a failure occurred because the ACC did not
467 handle the situation as they expected, through appropriate initiation of braking. For example,
468 the participants wrote “I didn't feel or hear the car decelerate, when I experienced it decelerate

469 before or where I would have chosen to start the process of decelerating” or “The distance
470 became shorter and the car didn't decelerate” or “The system tried to brake, but my reaction
471 was that the braking distance was too short.” Besides, 12 participants (24.5% of the sample)
472 recognized the failure because the distance to the lead vehicle decreased more than they would
473 have expected, as stated in these replies: “I was too close to the car in front” or “The car in front
474 of me got closer too quickly” or “I approached the vehicle in front of me too fast.” Finally, the
475 remaining participants did not notice a failure of the system (9 participants, 18,4% of the
476 sample) or identified a system failure different from the one simulated during the experiment
477 (1 participant, 2,0% of the sample).

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

482

483 4. Fitting and comparison of the computational driver models

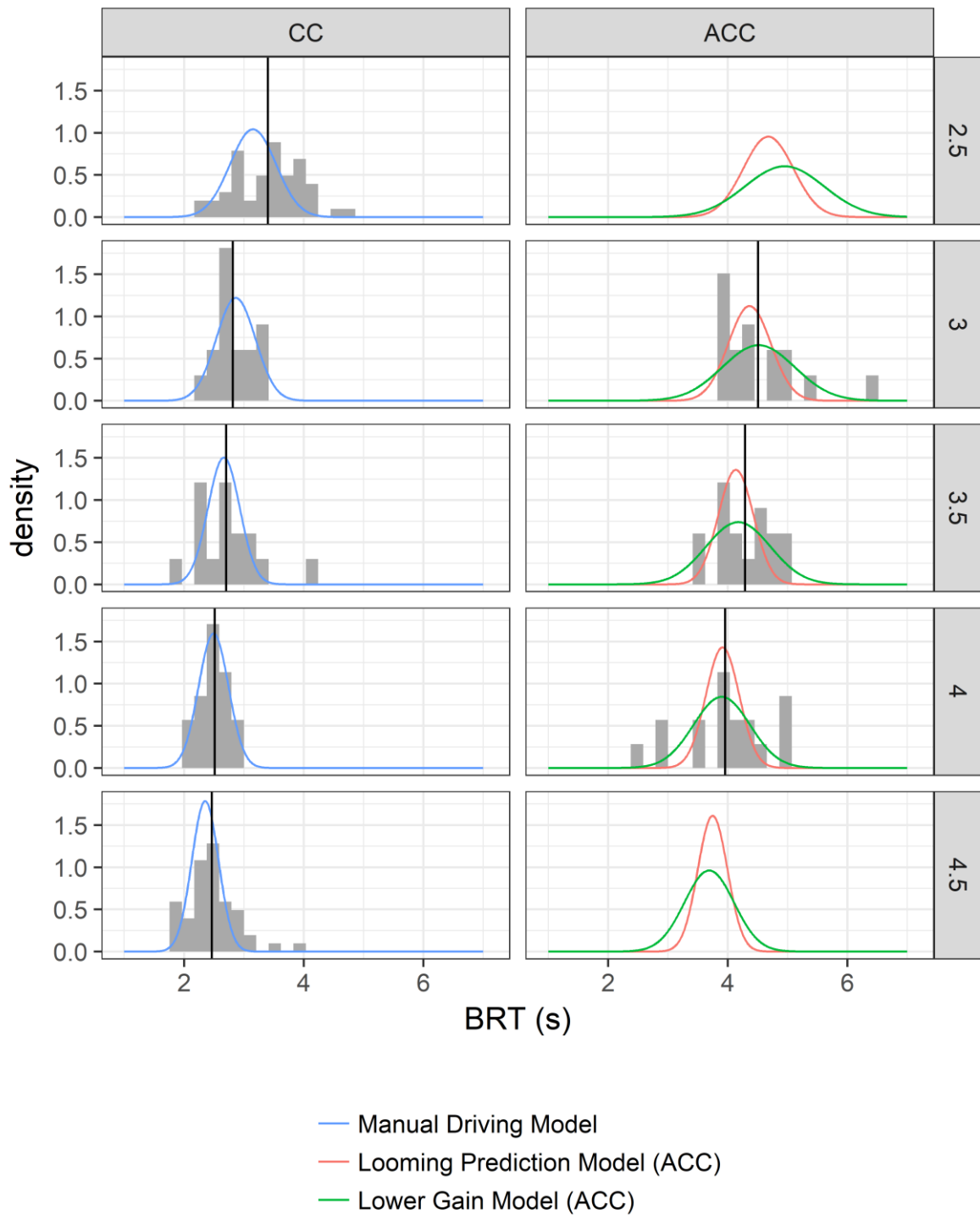
484 As reported in section 3.2.1, the a priori computational models do not accurately predict the
485 absolute BRTs from the driving simulator study. To yield better predictions of BRTs, and to
486 allow a detailed model comparison, the models were fitted to the driving simulator data. First,
487 the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

499

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

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

502



503

504 **Figure 9: Distribution (histograms) and average values (vertical lines) of BRTs from the driving**
505 **simulator study and distributions of BRTs predicted by the fitted computational models (curves) as**
506 **a function of kinematic criticality (deceleration values from 2.5 to 4.5 m/s²) and system (CC or ACC).**
507 **For the driving simulator data, only the first three events (the first encounter of each kinematic**
508 **criticality) were included in the figure. Besides, the distributions of BRTs from the driving simulator**

509 **study are not reported for deceleration values of 2.5 and 4.5 m/s² during driving with ACC, due to**
510 **the small number of drivers braking.**

511

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

524

525 5. Discussion

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

537 The predictions of the computational models yielded shorter BRTs with increase of kinematic
538 criticality for all models and a delay in BRTs during driving with ACC compared to driving

539 manually. In the models, this delay originated from a slower accumulation of looming
540 prediction error either due to drivers' expectations of ACC braking (looming prediction model),
541 in line with the framework of *predictive processing* (e.g., Clark, 2013; Clark, 2016; Friston et
542 al., 2010; Engström et al., 2018), or due to lower arousal (lower gain model) caused by
543 monitoring of the ACC system, inducing passive fatigue (Desmond & Hancock, 2001; Greenlee
544 et al., 2018; Saxby et al., 2013; see also Markkula and Engström, 2017).

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

- 550 • The BRTs significantly decrease with higher levels of kinematic criticality, both during
551 driving with CC and ACC. This outcome is in line with previous research (Markkula,
552 2014; Markkula et al., 2016; Markkula & Engström, 2017; Engström et al., 2017;
553 Venkatraman et al., 2016) but shows for the first time this phenomenon in silent failures
554 of automation.
- 555 • The BRTs are significantly longer during driving with ACC compared to driving with
556 CC. However, the a priori models' BRTs predictions were longer than the ones observed
557 in the driving simulator study, with this difference ranging between 0.7 and 0.9 seconds.
558 This difference could possibly be explained by the fact that the previous experiments
559 used to parameterize the manual driving model (Engström et al., 2010; Ljung Aust et
560 al., 2012; Markkula et al., 2013; Markkula et al., 2016; Nilsson et al., 2018) had different
561 driving conditions. Most notably, these past studies only considered BRTs for
562 unexpected lead vehicle events, whereas the present driving simulator study had
563 repeated scenario exposures, for which response times are known to be reduced (Lee et
564 al., 2002; Ljung Aust et al., 2013). Also, in past studies, the critical scenario was
565 different (lead vehicle braking after cutting in), the manual driving was performed
566 without CC, and the considered lead vehicle decelerations were also higher compared
567 to the current driving simulator study.

568 The subjective data collected after the rides in the driving simulator suggest that most of the
569 drivers reacted, during the emergency rear-end situations, due to a mismatch between the
570 expected and the perceived visual cues, when the silent failure of ACC occurred: the drivers

571 expected the ACC to brake and/or maintain a constant time headway (referred as ‘distance’ by
572 the participants) to the lead vehicle but the visual cues perceived from the environment revealed
573 to the drivers that “The distance became shorter and the car didn't decelerate.” This outcome
574 might provide support for the looming prediction model since the drivers seemed to embody a
575 generative model of ACC working principle, although probably still a basic one considered the
576 short experience in driving with the system. Besides, it underlines the importance of appropriate
577 drivers’ prediction/expectation about the actions (e.g. braking or steering) undertaken by
578 automated driving systems or driving automation systems (Engström et al., 2018; Victor et al.,
579 2018).

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

599 Overall, the present study provided new insights into driver braking reactions in rear-end
600 critical situations originated by automation failures. The key novel contribution of the present
601 paper is the proposal of two computational driver models, parametrized based on driving
602 simulator data, which were both found to be capable of accounting for the delay in drivers’

603 responses to silent ACC failures, compared to driving with CC. These models can then be
604 applied in computer simulations aiming to assess the safety benefits of active safety systems or
605 automated driving (Bärgman et al., 2017; Kusano & Gabler, 2012; McLaughlin et al., 2008).

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

633

634 Key points

- 635 • Three computational driver models were described and applied in simulations to predict
636 BRTs in rear-end critical scenarios, induced by different levels of lead vehicle
637 deceleration: one *manual driving model* to predict BRTs during manual driving (or
638 during driving with CC) and one *looming prediction model* and one *lower gain model*
639 to predict BRTs during driving with ACC. The looming prediction model assumes that
640 drivers embody a generative model of ACC while the lower gain model assumes that
641 drivers' arousal decreases due to monitoring of the automated system.
- 642 • A driving simulator study was conducted with 49 participants to test the predictions of
643 BRTs issued by the three computational driver models. The study confirmed the
644 predictions of the models: BRTs were significantly shorter with an increase in kinematic
645 criticality, both during driving with CC and ACC and BRTs were significantly delayed
646 when driving with ACC compared to driving with CC. However, the predicted BRTs
647 were longer than the ones observed in the study and, for this reason, a fitting of the
648 models to the data from the driving simulator study was performed.
- 649 • Both the fitted *looming prediction model* and the *lower gain model* predicted well the
650 BRTs obtained from the driving simulator study in the chosen range of lead vehicle
651 decelerations. Although the *lower gain model* performs better based on the Akaike
652 Information Criterion (AIC), the *looming prediction model* has the advantage of being
653 able to predict the average BRTs, directly using parameters of the model fitted to the
654 CC driving data.
- 655 • The models resulting from this study can have application in computer simulations
656 aiming to assess the safety benefits of active safety systems or automated driving.

657

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665

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