

## Driving simulator evaluation of an advance warning system for safe cyclist overtaking

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### ABSTRACT

Among all crashes involving cyclists, a motorist approaching a cyclist on a shared lane from behind is particularly dangerous and likely to result in serious injuries and fatalities. Previous research has highlighted that inadequate lateral distance and high vehicle speed are among the main contributing factors of crashes involving cars overtaking cyclists.

Since new technology innovations offer the potential to increase safety and mobility, a driving simulator study was conducted to evaluate the safety effects of an advanced driver-assistance system (ADAS) for cyclist overtaking. The ADAS was composed by a multimodal human-machine interface (HMI) using a multistage collision warning system, informing drivers well in advance about the potential danger so that an imminent cyclist collision can be avoided. Three warning priority phases were defined: (1) normal, (2) danger, and (3) avoidable accident. Both visual and acoustic signals were used to warn drivers. A combination of Lateral Clearance (LC) and Time-To-Danger (TTD) parameters was used as ADAS activation criterion.

A general linear model showed a positive effect on the lateral clearance of the following variables: presence of the ADAS system, familiarity with the system, male gender, driving experience as car driver, and driving experience as cyclist. A negative effect was associated with the following variables: cyclist manoeuvring from the edge of the lane to the centre of the lane,

21 cyclists riding in parallel, driver's age, and self-reported aggressive driving. In conclusion, the  
22 drivers' characteristics affected the LC and the ADAS significantly increased LC, indicating a  
23 positive safety effect on cyclist overtaking by cars. No significant effect on speed during  
24 overtaking was observed between the condition with or without ADAS, although it was observed  
25 that men drove on average faster than women.

26 **Keywords:** cyclist overtaking, ADAS, multilevel warning, lateral clearance, speed.

## 27 **1 INTRODUCTION**

28 Cycling is a sustainable and affordable transport mode which has major health, environmental,  
29 and economic benefits. In recent years, there has been a growing trend of bicycling in Europe  
30 and the United States (McKenzie, 2014; Pucher and Buehler, 2017), making car-cyclist  
31 interactions an important focus for future traffic-safety improvements (Kovaceva et al., 2018).  
32 In 2016, about 25,600 people were killed in road accidents throughout the Europe, with 2,015  
33 people riding cycles (equal to 8% of the total number of road accident fatalities). In the same  
34 year, the total number of road crashes in the EU countries showed a significant decrease (40%)  
35 from 2007, while the number of crashes involving cyclists is not decreasing (only 24%) at the  
36 same rate (European Commission, 2018).

37 Studies show that the overall public health benefits of more cycling outweigh negative health  
38 impacts of increased crash risk. Nevertheless, the growing number of cyclists requires new  
39 approaches to traffic management and investment into safe cycling infrastructure to improve  
40 road safety and reduce fatalities and injuries (IRTAD, 2018).

41 Cyclists are one of the most physically vulnerable road user groups, particularly when they share  
42 the road with motorized vehicular traffic. Their vulnerability as road users stems from their  
43 limited protection in the event of a collision and their low tolerance to the forces associated  
44 with collisions with motor vehicles. During a car accident involving a cycle, kinetic energy is

45 transferred from the vehicle to the “unprotected” cyclist. Part of this energy will be 'absorbed'  
46 by the cyclist' human body. When the amount of external forces exceeds the physical threshold  
47 tolerated by the human body, severe or fatal injury will occur. Weight (mass) and speed play a  
48 very prominent role in the released energy in the collision. When the collision speed increases,  
49 the amount of energy that is released increases as well. When a car and a bicycle collide, the  
50 difference in mass is huge and the collision energy is mainly absorbed by the lighter vehicle, so  
51 its occupants will have the greatest risk of serious injuries or even fatalities (Broughton, 2005;  
52 SafetyNet, 2007).

53 Among all types of crashes involving cyclists, a motorist approaching a cycle from behind is  
54 particularly dangerous and much more likely to result in serious injuries and fatalities (Feng et  
55 al., 2018). When cars and cyclists share the same lane, cars typically need to overtake them,  
56 creating dangerous Interactions. These interactions often result in severe injuries or even  
57 fatalities, especially on rural roads, due to the large difference between speeds of the car and  
58 cycle (Farah et al., 2019; Kovaceva et al., 2018; Behnood and Mannering, 2017). Moreover, an  
59 overtaken cyclist is subject to a lateral force that may lead to her/his wobbling or falling (Llorca  
60 et al., 2014). This force increases with speed of the motor vehicle and decrease with lateral  
61 distance from cycle, but it is estimated to be problematic only at the highest speeds and  
62 proximities (Shackel and Parkin, 2014).

63 The passing manoeuvre is affected by a range of factors involving the cyclist, road configuration,  
64 traffic, and vehicle (Feng et al, 2018). To minimize risky car-cyclist interactions during overtaking,  
65 motorists try to choose safe and comfortable lateral distance from the cyclist, lateral clearance  
66 (LC). Several studies have highlighted the critical importance of the LC for objective and  
67 subjective safety while passing a cyclist (Rubie et al., 2020). However, although LC is definitely a  
68 key indicator of safety, an overtaking manoeuvre is a long and complex process which is not

69 limited to the phase in which the vehicle moves parallel to the cycle, so the manoeuvre cannot  
70 be fully described by transient lateral clearance alone (Dozza et al., 2016).

71 To minimize the risk for cyclists from motor vehicles passing too close and to increase cyclist  
72 comfort, minimum passing distance laws (often referred to as 'one metre rules') have been  
73 introduced in some European countries, such as Belgium, France, Germany, Portugal and Spain,  
74 in 28 American states and in a number of U.S. cities, and in many other countries (several  
75 provinces of Canada, some states and territories of Australia, etc.) (Dozza et al., 2014; National  
76 Conference of State Legislatures, 2014; Shackel and Parkin, 2014). However, failure to follow  
77 traffic regulation, distracted driving and inability to determine passing distance accurately mine  
78 the effectiveness of this law. So, the being overtaken too close continue to be a major barrier to  
79 getting more people cycling, especially less confident cyclists, women, older people and  
80 children.

81 New technology innovations and automation in driving tasks offer the potential to increase  
82 safety and mobility (Hagenzieker et al., 2019). Moreover, in-vehicle information systems (IVIS)  
83 and advanced driver assistance systems (ADAS) have been developed with the clear intent to  
84 improve driving behaviour and foster road users' comfort and safety, anticipating accidents to  
85 avoid them or reduce their severity.

86 In the context of ADAS systems, the human-machine interface (HMI) serves as a communication  
87 bridge between the vehicle and the driver and its optimal design play a decisive role to ensure  
88 the effectivity and the safety of such systems. The way the information is presented as well as  
89 the right timing are the two crucial factors for the design of a warning systems (Cao et al., 2009).

90 A promising way to reduce transmission errors and enhance safety seems to be presenting  
91 information to drivers via multiple modalities, e.g. visual, auditory, or haptic warning (Schwarz  
92 and Fastenmeier, 2017). It can be assumed that different modalities should complement each

93 other presenting one message (Cao et al., 2009). After receiving a warning message, drivers need  
94 certain amount of time for reacting and then performing appropriate actions to avoid the crash.  
95 Therefore, the delivery time of warning messages could seriously influence the effectiveness of  
96 the warning system (Yan et al., 2015). A warning presented too early might be interpreted by  
97 drivers as a false alarm and may eventually be ignored, leading to driver distraction or  
98 annoyance (Brown et al., 2001; Winkler et al., 2016). On the contrary, if the system warns drivers  
99 too late, there is not enough time for them to detect the warning, chose an avoidance response  
100 and take action to avoid or mitigate the collision. Compared to a single warning stage of  
101 imminent danger level, a multistage concept extends the warning range to more advanced  
102 cautionary levels of pre-warning or simply informing drivers about a safety-critical situation  
103 ahead. Thereby, a multistage warning can induce different driver reactions depending on the  
104 urgency level and the situation's intervention need with adapted intrusiveness. The early  
105 warning stages should be less intrusive as they might be triggered more frequently and would  
106 otherwise increase the probability of annoying drivers, whereas later warning stages certainly  
107 need a stronger salience to certainly elicit a driver reaction in an emergency (Winkler et al., 2016;  
108 Winkler et al., 2018).

109 In this study, as part of the European Horizon 2020 project i-DREAMS ([www.idreamsproject.eu](http://www.idreamsproject.eu)),  
110 a new multistage ADAS system supporting drivers as they overtake cyclists was designed to  
111 improve cyclists safety and comfort. The proposed driver aid system is characterized by a  
112 multimodal HMI using a multistage collision warning approach. The warning strategy is based  
113 on a combination of lateral clearance (LC) and time-to-danger (TTD) to guarantee both lateral  
114 and longitudinal control of vehicle during overtaking. Finally, a medium-fidelity driving simulator  
115 experiment was carried out to study the effect of driver's characteristics on car-to-cyclist  
116 overtaking behaviour and to evaluate the effectiveness and safety benefits of the designed in-  
117 vehicle driving assistance system in some potentially critical car-cyclist overtaking scenarios.

## 118 2 EXPERIMENT

119 The driving simulator experiment was developed as a 2 (ADAS) x 3 (Event) repeated measures  
120 design. The within-subject variables are: ADAS (2 level: without and with cyclist overtaking  
121 assistance system) and Events (three car-cyclist overtaking situations: a cyclist rides close to the  
122 outer edge of roadway, a cyclist swerves left and two cyclists riding side-by-side).

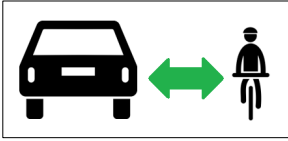
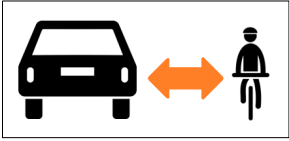
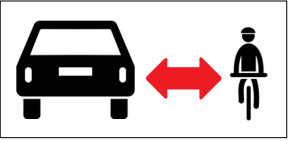
### 123 2.1 Car-cyclist overtaking ADAS system

124 An ADAS system was designed to support drivers keeping a safe and comfortable lateral distance  
125 when overtaking cyclists. The system consists of a multimodal Human-Machine Interface (HMI)  
126 using a multistage collision warning strategy timely making drivers aware of the presence of  
127 cyclists ahead and alerting the driver of the potential danger or an imminent collision when  
128 passing too close to cyclists. With this aim, three warning phases were defined:

- 129 (1) *Normal driving*: the driver is informed of the presence of a cyclist ahead at a safe lateral  
130 distance; no action is required by the driver;
- 131 (2) *Danger phase*: the driver is warned to an emerging risk situation which requires  
132 immediate attention and may require a corrective action;
- 133 (3) *Avoidable accident phase*: the driver is alerted to a critical situation which requires  
134 his/her immediate action or decision to avoid a potential crash.

135 The system alerts drivers using a combination of both visual and acoustic signals (Figure 1)  
136 positioned in a Head-up Display (HUD) projected on the vehicle's windshield. The visual  
137 information consists of a pictogram displaying front view symbols of a car and a cyclist separated  
138 by a double arrow which changes colour in each of the three warning phases and nudges the  
139 driver toward a corrective action. The normal driving condition is signaled only by a pictogram  
140 with green double arrow. The danger phase is introduced by an orange double arrow along with

141 a beep sound to warn inattentive drivers. A red double arrow coupled with a high pitched  
 142 double-beep sound is used to alert drivers in the avoidable accident phase.

Phase	Normal driving	Danger phase	Avoidable accident phase
Signal			
Visual			
Audio	No acoustic signal	Single Beep	Double high-pitched beep

143 **Figure 1.** ADAS warning phases

144 An overtaking maneuver is a long and complex process which is not limited to the phase in which  
 145 the vehicle moves parallel to the bicycle. Hence, the manoeuver cannot be fully described by  
 146 transient lateral clearance alone but both lateral and longitudinal control of vehicle have to be  
 147 taken into account (Dozza et al., 2016). For these reasons, a combination of lateral clearance  
 148 (LC) and Time-to-Danger (TTD) was chosen to define the three phases of the warning strategy.

149 The LC is used to monitor the lateral control of the vehicle and the minimum lateral distance  
 150 between the cyclist and the vehicle while passing (Dozza et al., 2016). The longitudinal control  
 151 of the motor vehicle is monitored using TTD, an extension of the Time-To-Collision (TTC)  
 152 measure that does not require the road users to be on collision course. In fact, TTC is an effective  
 153 measure to discriminate critical from normal behaviour and it is the time left to collision  
 154 between two vehicles if they continue at their present speed and on the same path (Hegeman  
 155 et al., 2009; Johnsson et al., 2018). Instead, the proposed measure TTD, is defined, in case of  
 156 cyclist overtaking by car, as the time required for the vehicle to laterally align its front bumper  
 157 with the rear wheel of the bike if they continue at their present speed:

$$158 \quad TTD = \frac{Dist_{vh-c}}{Speed_{vh} - Speed_c} \quad (1)$$

159 where  $Dist_{vh-c}$  is the distance (m) between the front bumper of the vehicle and the rear wheel  
160 of the cyclist,  $Speed_{vh}$  is the longitudinal velocity (m/s) of the vehicle, and  $Speed_c$  is the  
161 longitudinal speed (m/s) of the cyclist.

162 The optimal timing and distance to activate the three warning phases was designed after a  
163 comprehensive review of the literature and a pilot study. Considering that, in most European  
164 countries, the motorists are obliged by law to pass cyclists no closer than 1.5 metres in rural area  
165 (or on a road with a speed limit of 50 km/h or higher), and 1.0 m in urban areas (or on a road  
166 with a speed limit under 50 km/h) (Dozza et al., 2014; National Conference of State Legislatures,  
167 Tarko, 2018), the following LC threshold values have been adopted on rural roads: (1)  $LC \geq 1.5$   
168 m; (2)  $LC \geq 1.0$  m and  $LC < 1.5$  m; and (3)  $LC < 1.0$  m.

169 According to literature, a TTC threshold value of 4.0 s – 4.5 s can be considered an ideal trade-  
170 off in the context of a collision warning (Aksan et al., 2016; Li et al., 2014; Zheng et al., 2020; Yan  
171 et al., 2015). Moreover, TTC values greater than 4.0 or 5.0 s resulted in too many false alarms,  
172 while a TTC value of 3.0 s produced the least number of false alarms although in some cases  
173 critical situations were observed (Bella and Russo, 2011; Minderhoud et al., 2001). A TTC value  
174 of 2.0 s – 2.5 s should be considered as the absolute minimum to provide enough response time  
175 for the driver (Yan et al., 2015). Finally, TTC value of 1.0 s was assumed to be a useful measure  
176 of serious conflicts, in which the collision can hardly be avoided (Naujoks et al., 2016;  
177 Reinmueller and Steinhauser, 2019). Based on the previous considerations, the following TTD  
178 threshold values have been chosen: (1)  $TTD_{vh} \geq 3.0$  s and  $TTD_{vh} < 4.5$  s; (2)  $TTD_{vh} \geq 2.0$  s and  
179  $TTD_{vh} < 3.0$  s; and (3)  $TTD_{vh} < 2.0$  s.

180 Finally, the activation criterion of the three warning phases during cyclists overtaking maneuver  
181 results as a combination of the following lateral clearance (LC) and time-to-danger (TTD)  
182 threshold values (Table 1).



183

**Table 1.** Warning criterion as combination of LC and TTD

		Time to Danger		
		$4.5\text{ s} > TTD_{vh} \geq 3\text{ s}$	$3\text{ s} > TTD_{vh} \geq 2\text{ sec}$	$TTD_{vh} < 2\text{ s}$
Lateral Clearance	$LC \geq 1.5\text{ m}$	Normal diving	Normal diving	Normal diving
	$1.5\text{ m} > LC \geq 1.0\text{ m}$	Normal diving	Danger phase	Danger phase
	$LC < 1.0\text{ m}$	Normal diving	Danger phase	Avoidable Accident phase

184

185 **2.2 Apparatus**

186 The study was conducted on a fixed-base, medium-fidelity driving simulator (STISIM Drive v3 ;  
 187 Systems Technology Incorporated) at the Transportation Research Institute (IMOB) of Hasselt  
 188 University in Belgium. It consists of a real vehicle cabin (Ford Mondeo) with a force-feedback  
 189 steering wheel, brake and accelerator pedals, and automatic transmission. The visual scene was  
 190 projected to a three-channel 180 degrees forward field of view seamless half-cylindrical screen,  
 191 with on-screen projected rear- and side-mirrors. A spatial sound system renders the own  
 192 vehicle’s engine, the noise from tires and from surrounding traffic. The simulation included  
 193 vehicle dynamics, visual, acoustic and tactile feedback and a performance measurement system.

194 **2.3 Virtual road design**

195 In the experiment, a two-lane rural highway with lane width of 3.00 m and no shoulders was  
 196 simulated, according to the Belgian Road Design Standard (Departement Mobiliteit en Openbare  
 197 Werken, 2017).

198 The experimental route consisted of 10 successive tangents with length equal to 1,000 m and 9  
 199 circular curves with 400 m radius and 35° deflection angle. The tangent-to-curve transition is  
 200 carried out by spiral curves with a length equal to 55 m, which corresponds to 2.0 s at 100 km/h.  
 201 The edge lines are continuous for the whole experimental road while the centre line is

202 continuous from 150 m prior to 150m after each curve and dashed elsewhere. Speed limit signs  
203 of 70 km/h are posted at the start and repeated regularly along the experimental road. No  
204 separated/dedicated cycle lane was designed. Hence, motor vehicles had to share lanes with  
205 cyclists, interacting with each other. No symbols, signs or markings were installed on the road  
206 surface to advice the presence of cyclists on the road. The surroundings were modelled to mimic  
207 a real rural environment.

208 With the aim to study the effectiveness of the proposed in-vehicle warning system, the following  
209 three cyclist passing situations (Figure 2) were tested: Event 1 (E1): overtaking a cyclist where  
210 the cyclist keeps a constant lateral position (close to the road edge line); Event 2 (E2): overtaking  
211 a cyclist that manoeuvres from the outer edge of the lane to the centre of the lane; and Event 3  
212 (E3): overtaking two cyclists riding side by side (one close to the edge line and the other one on  
213 the center of the lane). The overtaken cyclists keep a constant speed of 18 km/h during all the  
214 events.



215 **Figure 2.** Tested overtaking events during the experiment

## 216 **2.4 Experimental procedure**

217 The best-case scenario in terms of visibility, road and weather conditions was simulated, such  
218 as dry pavement conditions and a good state of maintenance, high visibility, sun light, etc.  
219 Occasional traffic going in the opposite direction was simulated to improve the scenario realism.

220 The protocol was approved by the Social and Societal Ethics Committee of Hasselt University  
221 (approval number: REC/SMEC/JA/189-132). Upon their arrival in the laboratory, each participant  
222 was briefed on the requirements of the experiment and an informed consent was obtained  
223 before conducting a pre-driving questionnaire (biographical and driving style information and  
224 knowledge/use of ADAS systems). Before the actual simulator experiment, participants were  
225 instructed to familiarize with the driving simulator system.

226 After a short break, each participant drove twice the same experimental route, first without and  
227 then with the ADAS cyclist overtaking system. During each drive, each participant was engaged  
228 in nine car-cycle overtaking events resulting from the three-time repetition of each basic event  
229 (E1, E2 and E3). To prevent confounding factors and to avoid any systematic order effects, the  
230 order of application of the 3 events to the experimental units (participants) was determined  
231 randomly. The sequence in which participants encountered each event through the  
232 experimental route was counterbalanced to minimize the presentation order effect. Also, it is  
233 guaranteed that, when all drivers had completed the experiment, each event was encountered  
234 the same number of times (3) in each driving order. Random extraction was performed through  
235 R-cran, designing a different scenario for each driver.

236 At the end of the two driving sessions, each participant filled a post-driving questionnaire on the  
237 personal assessment of the tested ADAS system (including items of effectiveness, reliability,  
238 utility, ease-to-use and willingness-to-buy). Simulator sickness questionnaires (Kennedy et al.,  
239 1993) were also filled by each participant before the simulator familiarisation session and after  
240 the driving sessions to screen potential simulator discomfort.

## 241 **2.5 Participants**

242 Fifty participants took part in the study voluntarily, without any financial compensation. Two  
243 participants have been excluded from all further analysis (one due to an error in data logging,

244 the other one because it was detected to be an outlier through the Grubbs test) leading to a  
 245 sample size of 48 participants. No simulator sickness was observed. Moreover, the sample is  
 246 composed of 21 women and 27 men, ranging in age from 19 to 66 years (mean = 32.44, standard  
 247 deviation = 9.33). All the participants had a valid driving licence and at least 1 year of driving  
 248 experience (mean = 11.94, standard deviation = 9.23). More than 60% of participants drive at  
 249 least once a week, while about 30% occasionally drive . Participants rated their driving style on  
 250 a scale of 1 (very defensive) to 5 (very offensive) (mean = 3.04, standard deviation = 0.90). More  
 251 than 90% of the sample was aware of driver warning/assistance systems and about 40% had  
 252 experienced at least once a driving aid system but, finally, only 25% use them frequently in their  
 253 everyday driving.

254 **Table 2.** Driver characteristics: numerical variable

<b>Numerical Variable</b>	<b>Mean</b>	<b>St. dev</b>	<b>Min</b>	<b>Max</b>
Age	32.44	9.43	19.00	66.00
Years of driver license	11.83	9.42	1.00	47.00
Number of serious crashes, as a driver, in the past 3 years	0.02	0.14	0.00	1.00
Number of slight crashes, as driver, in the past 3 years	0.25	0.44	0.00	1.00
Defensive driving (subjective assessment of driving style)	3.04	0.90	1.00	5.00

255

256 **Table 3.** Driver characteristics

<b>Categorical variable</b>	<b>Categories</b>	<b>#</b>	<b>%</b>
Gender	Female	27	56.25%
	Male	21	43.75%
Weekly driving frequency	Everyday	16	33.33
	2-4 times a week	13	27.08
	Every weekday	6	12.50
	Once a week	7	14.58
	Weekend only	3	6.25
	Occasionally'	3	6.25

	0	3	6.25
	1 - 5000	17	35.42
Average annual kilometers travelled by car	10001-20000	14	29.17
	5001-10000	9	18.75
	>30000	5	10.42
	Everyday	3	6.25
	2-4 times a week	15	31.25
Weekly cycling frequency	Every weekday	2	4.17
	Once a week	10	20.83
	Weekend only	3	6.25
	Never	15	31.25
	0	15	31.25
	1 - 50	19	39.58
Average annual kilometers travelled by bicycle	51-100	5	10.42
	101-175	5	10.42
	176-300	4	8.33
Knowledge about driver warning/assistance systems	Yes	45	93.75
	No	3	6.25
Frequent use of driver warning/assistance systems	Yes	12	25.00
	No	36	75.00
Used at least once a driver warning/assistance system	Yes	19	39.58
	No	29	60.42

257

### 258 3 ANALYSIS METHODS

259 Lateral clearance and speed were used both as measure of driving behaviour during passing and  
260 as measure of effectiveness of ADAS system. The hypothesis of the study was that the presence  
261 of both cyclist and the ADAS system influences the risk perception, so that drivers react to such  
262 stimuli changing their driving style in the different overtaking events. Statistical tests and

263 regression models with a random parameter were used to study the driver behaviour during  
264 car-bicycle overtaking and to evaluate the statistical significance of the experimental results.

### 265 **3.1 Statistical test**

266 Statistical inference tests were carried out to study of the effectiveness of the ADAS system,  
267 evaluating statistically significant differences in speed and lateral clearance. Speed and LC data  
268 were pre-processed testing the normality and homoscedasticity assumptions. Since different  
269 tests of normality often produce different results, we verified the normality assumption using  
270 the tests Anderson–Darling, Jarque–Bera, Kolmogorov–Smirnov, Lilliefors, and Shapiro–Wilk.  
271 Given the normality and homoscedasticity of the LC and speed data, ANOVA and t-student tests  
272 were used. The ANOVA showed a statistically significant overall effect. The t-tests showed  
273 significant differences among the events and an effect of the ADAS (Montella et al., 2015).

### 274 **3.2 Regression models with random effect**

275 The regression models with random effect were performed to analyse the relationship between  
276 the speed and lateral clearance with variables related at the presence of ADAS system, the type  
277 of event, and the driver characteristics. The data considered involved measurements over time  
278 for the same drivers and included time invariant variables, such as driver characteristic (i.e.  
279 gender, age, etc.). Regression models with random effects were developed to account for  
280 within-group dependence, using xtreg command of STATA software with the maximum-  
281 likelihood random-effects estimator (Robson and Pevalin, 2015):

$$y_{it} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \dots + \beta_p x_{pit} + v_{it} \quad (2)$$

282  $y_{it}$  denotes the value of the dependent variable  $Y$  for individual  $i$  ( $i = 1, \dots, N$ ) at time point  $t$   
283 ( $t = 1, \dots, T$ ),  $\beta_0$  is the intercept, the  $\beta_p$ ,  $i = 0, 1, \dots, p$ , are the regression coefficients,  $v_{it}$  is  
284 the error term which consists of two components ( $v_{it} = u_i + e_{it}$ ),  $u_i$  “unobserved

285 heterogeneity” component (individual specific but does not vary over time), and an  $e_{it}$   
286 idiosyncratic component (varies across both individuals and time).

287 These models were developed by stepwise approach, beginning with no explanatory variables  
288 in the model and sequentially adds one variable. At each stage it selects the term giving the  
289 greatest improvement in fit. A point of diminishing returns occurs in adding explanatory  
290 variables when new ones added are themselves so well predicted by ones already used that they  
291 do not provide a substantive improvement in the likelihood ratio (LR). The used criterion for the  
292 addition of variables is based on the partial  $G^2$ -statistic, given by:

$$LR = G^2 = -2 \log \left( \frac{LL_k}{LL_{k-1}} \right) = 2(\log LL_k - \log LL_{k-1}) \quad (3)$$

293 where  $LL_k$  is the likelihood of the model at k step and  $LL_{k-1}$  is the likelihood of the model at k-  
294 1 step. Variables were entered as long as the  $G^2$ -statistic p-value remains below 0.05. The  
295 procedure terminates when the addition of any of the remaining variables would yield a  $G^2$ -  
296 statistic p-value > 0.05, or when all variables have been entered. Later in the process, variables  
297 which were become non-significant after other variables have been added were excluded. The  
298 significance for the individual regression coefficient  $\beta_p$  was evaluated using the Wald statistic  
299 with a significance level of 0.10. However, to obtain a good and parsimonious model, Akaike  
300 information criterion (AIC) and Bayesian information criterion (BIC) were used.

301 Since the observations are not independent of each other, residuals are not independent and,  
302 therefore, common likelihood-based methods and other measures of model fit from ordinary  
303 linear regression need to be adjusted (Pagliara and Mauriello, 2017). To get around this problem,  
304 a number of statisticians have developed so-called ‘Pseudo  $R^2$ ’ measures that aim to mimic  
305  $R^2$  for logistic regression models. The most prominent one is McFadden’s Pseudo  $R^2$  is given by  
306 (Jobson, 2012):

$$\text{McFadden} - R^2 = 1 - \frac{LL_k}{LL_0} \quad (4)$$

307 The McFadden –  $R^2$  values are usually much smaller than  $R^2$  values in linear regression.  
 308 McFadden –  $R^2 < 0.05$  indicates low fit, McFadden –  $R^2 > 0.20$  indicates a very good fit, and  
 309 McFadden –  $R^2 > 0.40$  is hardly observed (Andreß et al., 2013).

## 310 **4 RESULTS AND DISCUSSION**

311 Speed and LC were analysed to study the driver behaviour during cyclist overtaking. Given the  
 312 normality and homoscedasticity of the speed and LC data, statistical tests and regression models  
 313 with random effects carried out to evaluate the influence of the ADAS system, the position of  
 314 the cyclists through the three events and the characteristics of the drivers reported in Tables 2  
 315 and 3.

### 316 **4.1 LC data**

317 The ADAS system produced a significant increase of the average total LC equal to 0.30 m (Table  
 318 4), and the ANOVA test showed a statistically significant overall effect (p-value<0.001, Table 5).  
 319 During baseline driving, LC (1.15 m) was smaller in event 2 (cyclist moving from the edge to the  
 320 centre of the lane) and larger (1.76 m) in event 1 (cyclist riding close to the edge). The t-tests  
 321 showed significant differences among the events and an effect of the ADAS. The ADAS  
 322 significantly increased LC in all events: from 1.76 to 2.19 m in event 1 (25%, p<0.001), 1.15 to  
 323 1.49 m in event 2 (29%, p<0.001), and 1.46 to 1.60 m in event 3 (10%, p=0.096).

324 **Table 4.** Mean and standard deviation of LC



Event	A0		A1		$\frac{(LC_{A1} - LC_{A0})}{LC_{A0}}$
	Mean LC [m]	St. Dev. [m]	Mean LC [m]	St. Dev. [m]	$LC_{A0}$
E1	1.76	0.65	2.19	0.55	24.58%
E2	1.15	0.48	1.49	0.46	29.24%
E3	1.46	0.41	1.60	0.37	9.87%
Total	1.46	0.58	1.76	0.56	20.90%

325

326

**Table 5.** LC: t and ANOVA tests

		A0			A1		
		E1	E2	E3	E1	E2	E3
A0	E1	1	<b>&lt;0.001</b>	<b>&lt;0.001</b>	<b>&lt;0.001</b>	<b>&lt;0.001</b>	<b>0.014</b>
	E2		1	<b>&lt;0.001</b>	<b>&lt;0.001</b>	<b>&lt;0.001</b>	<b>&lt;0.001</b>
	E3			1	<b>&lt;0.001</b>	0.499	<b>0.002</b>
A1	E1				1	<b>&lt;0.001</b>	<b>&lt;0.001</b>
	E2					1	<b>0.028</b>
	E3						1
<b>ANOVA</b>		<b>F statistic = 69.907, df1 = 5, df2 = 858, p-value = &lt; 0.0001</b>					

Note: In boldface statistically significant values were reported with 5% level of significance and in underline statistically significant values were reported with 10 % level of significance

327

328 The model showed (Table 6) that, the use of the ADAS system has a positive effect on LC with  
329 an increase of 0.30 m (p-value <0.001). Events E2 and E3 have a lower LC than event E1,  
330 respectively of 0.65 m (p-value <0.001) and 0.44 (p-value <0.001). The results of this model  
331 confirmed the ANOVA and t-Test. The driver characteristics (gender, age, weekly driving  
332 frequency and weekly cycling frequency) influenced the LC. LC was increased of 0.11 m (p-  
333 value=0.003) if the driver was a male and decreased of 0.012 m per year with age (p-  
334 value=0.037). Differences in overtaking behaviours, related to gender and age, were also found  
335 by Farah et al. (2011) where male and younger drivers had significantly higher desired driving  
336 speeds, and Llorca et al. (2017) found that higher speeds required larger LCs, although in our  
337 study a significant influence of car speed on LC was not found, in line with Dozza et al. (2015)  
338 and Mehta et al. (2015). Moreover, females perceived a greater risk for a head-on collision with  
339 the oncoming vehicle than a rear end or side -swipe collision with the cyclist (Rasch et al., 2020).

340 A positive effect on the LC was given by the weekly frequency of driving or cycling. Compared to  
 341 drivers who never drive during the week, the LC increased by 0.55 m (p-value = 0.004) for those  
 342 who drive every day, 0.72 m (p-value = 0.001) in the case of driving every weekday, 0.55 m (p-  
 343 value = 0.025) for drivers who use the car only on weekend, and 0.34 m (p-value = 0.0690) for  
 344 those who drive 2 to 4 times a week.

345 Compared to drivers who never use a bicycle in a week, the LC increased by 0.30 m (p-value  
 346 <0.001) for drivers cycling every day, and 0.20 m (p-value =0.099) for those who ride 2 to 4 times  
 347 a week. Those results are in line with the study of Fruhen & Flin (2015), in which it has been  
 348 shown that negative attitudes towards cyclists were more pronounced in non-cyclist motorists  
 349 than cyclist ones.

350 **Table 6.** LC: random effects model

Variables	Coef.	Std. Err.	z	P> z	
<b>ADAS</b>					
A1	0.304	0.025	12.090	<0.001	***
A0					
<b>Event</b>					
E2	-0.650	0.031	-21.060	<0.001	***
E3	-0.444	0.031	-14.390	<0.001	***
E1					
<b>Gender</b>					
Male	0.111	0.037	2.98	0.003	**
Female					
<b>Age</b>					
	-0.012	0.0058	-2.09	0.037	**
<b>Weekly driving frequency</b>					
Everyday	0.546	0.191	2.860	0.004	**
Every weekday	0.720	0.220	3.270	0.001	**
Weekend only	0.545	0.243	2.240	0.025	**
2 or 4 Times a week	0.339	0.187	1.820	0.069	*
Once a week	0.215	0.200	1.080	0.282	
Never					
<b>Weekly cycling frequency</b>					
Everyday	0.303	0.077	3.950	<0.001	***
Every weekday	-0.282	0.248	-1.130	0.256	
Weekend only	-0.009	0.186	-0.050	0.962	

2 or 4 Times a week	0.204	0.124	1.650	0.099	*
Once a week	0.071	0.129	0.550	0.582	
Never					
<hr/> _cons	1.833	0.271	6.750	<0.001	***
<hr/> $\sigma_u$	0.256	0.029			
$\sigma_e$	0.370	0.009			
<hr/> $\rho_0$	0.323	0.051			

Note: \*\*\* indicates statistically significant values with p-value<0.01, \*\* indicates statistically significant with p-value < 0.05 level of significance and \* with p-value< 0.1

351

352 The McFadden –  $R^2$  was equal to 0.36 (Table 7), and as reported by Anderson et al. (2013), this  
353 value indicated a very good of fit. This result was also confirmed by LR test performed comparing  
354 the fit at convergence model to the fit at constant model. LR test statistic likelihood ratio test  
355 between full and constant models ( $LR \frac{\text{full model}}{\text{constant model}} = 479.14$  with p-value <0.001) showed that  
356 the full random model fitted significantly better than the model with only constant. The value  
357 of the intra class correlation,  $\rho_0$ , evidenced that 32.3% of the variance was due to differences  
358 within drivers. The likelihood ratio test of  $\sigma_u = 0$  was testing the null hypothesis that the standard  
359 deviation of the random intercept was equal to zero. The value of the likelihood ratio test of  
360 homoscedasticity ( $LR \text{ test } \sigma_u = 0$ ) was equal to 229.05 (p-value<0.001), highlighting the  
361 necessity to use random model.

362

**Table 7.** LC: Model statistics

Parameter	Value
Obs	864
Log-likelihood at constant - random model	-661.090
Log-likelihood at convergence – random model	-421.519
LR1 - random model at convergence vs. random model at constant	479.14
Prob(LR1, df=15)	<0.001
McFadden – $R^2$	0.362
$LR \text{ test of } \sigma_u = 0$	229.05
Prob(LR2, df=1)	<0.001
AIC	879.037
BIC	964.746

363

364 **4.2 Speed data**

365 The ADAS system produced a decrease of the average total speed equal to 0.4 km/h (Table 8),  
 366 and the ANOVA test showed a not statistically significant overall effect (p-value= 0.15, Table 9)).  
 367 The ANOVA result was confirmed by the student’s t-tests. The p-value of the paired t-test, for  
 368 all 3 events (A0 vs A1), was higher than 0.10, having to accept the hypothesis that there was no  
 369 statistically significant difference between the two conditions. However, the paired t-test  
 370 showed that both in the baseline condition (A0) and with the use of the ADAS system (A1), there  
 371 was a significant difference between E1 and E2 with lower speed in E2 event. In the baseline  
 372 condition (A0), the mean speed difference between the two overtaking events was of 3.74 km /  
 373 h (p-value = 0.067), while, if the ADAS system is active (A1), the average speed of E2 was 4.00  
 374 km / h lower than E1 ( p-value = 0.03).

375 **Table 8.** Mean and standard deviation of Speed

Event	A0		A1		$\frac{(Speed_{A1} - Speed_{A0})}{Speed_{A0}}$
	Mean Speed [hm/h]	St. Dev. [hm/h]	Mean Speed [hm/h]	St. Dev. [hm/h]	
E1	78.52	17.35	77.98	16.82	-0.68 %
E2	74.78	17.20	73.98	17.16	-1.06 %
E3	76.13	15.39	76.29	15.46	0.20 %
Total	76.48	16.70	76.08	16.54	-0.51 %

376 **Table 9.** Speed: t and ANOVA tests

		A0			A1		
		E1	E2	E3	E1	E2	E3
A0	E1	1	<u>0.067</u>	0.219	0.791	<b>0.026</b>	0.250
	E2		1	0.480	0.111	0.695	0.434
	E3			1	0.332	0.263	0.933
A1	E1				1	<b>0.047</b>	0.374
	E2					1	0.232
	E3						1
<b>ANOVA</b>		F statistic = 1.621, df1 = 5, df2 = 858, p-value = 0.152					

Note: In boldface statistically significant values were reported with 5% level of significance and in underline statistically significant values were reported with 10 % level of significance

377 The model statistics and estimated parameters for regression model with random effects are  
 378 reported in Table 10 & 11. Non-significant parameters were not included in the model and were  
 379 not reported. The results of this model confirmed the ANOVA and t-Test, no dependence was  
 380 found with the use of ADAS, while for E2 there was a speed reduction of 3.87 km / h (p-value  
 381 <0.001). In addition, the dependence of speed with gender was identified, men drove 5.21 km /  
 382 h (p-value <0.001) faster than women. The McFadden –  $R^2$  was equal to 0.003, although this  
 383 value indicated a low fit, likelihood ratio test between full and constant models ( $LR \frac{\text{full model}}{\text{constant model}} =$   
 384 22.54 with p-value <0.001) showed that the full random model fitted significantly better than  
 385 the model with only constant. The value of the intra class correlation,  $\rho_0 = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_e^2}$ , evidenced  
 386 that 61.3% of the variance was due to differences within drivers. The value of the likelihood ratio  
 387 test of homoscedasticity ( $LR \text{ test } \sigma_u = 0$ ) was equal to 657.97 (p-value<0.001), highlighting the  
 388 necessity to use random model.

389 **Table 10.** Speed: Random effects model

Variables	Coef.	Std. Err.	z	P> z	
<b>Event</b>					
E2	-3.87204	0.846273	-4.58	<0.001	***
E3	-2.03919	1.363712	-1.5	0.135	
E1					
<b>Gender</b>					
Male	5.205	1.122	4.64	<0.001	***
Female					
_cons	70.118	6.223	11.27	<0.001	***
$\sigma_u$	12.784	1.351			
$\sigma_e$	10.155	0.251			
$\rho_0$	0.613	0.052			

Note: \*\*\* indicates statistically significant values with p-value<0.01, \*\* indicates statistically significant with p-value < 0.05 level of significance and \* with p-value< 0.1

390 **Table 11.** Speed: Model statistics

Parameter	Value
Obs	864
Log-likelihood full model	-3321.2271

Log-likelihood constant model	-3309.9547
$LR \frac{\text{full model}}{\text{constant model}}$	22.54
Prob(LR1, df=3)	<0.001
McFadden – $R^2$	0.003
$LR \text{ test of } \sigma_u = 0$	657.97
Prob( $LR \text{ test of } \sigma_u$ , df=1)	<0.001
AIC	7285.879
BIC	7304.925

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391

## 392 5 CONCLUSION

393 The study showed that the ADAS system tested in the driving simulator experiment had  
394 significant effects on driver behaviour during a cyclist overtaking manoeuvre. The lateral  
395 clearance was affected significantly by the presence of the ADAS system with an increase of 0.30  
396 m equal to 20.90%. The ADAS system helped drivers to keep on average a lateral clearance  
397 greater for all three events. It is noteworthy that the ADAS was effective to help drivers to keep  
398 on average a lateral clearance greater than or equal to 1.5 m, that represents the minimum  
399 distance law when passing cyclists on rural area introduced in most European country (Dozza et  
400 al., 2014; Shackel and Parkin, 2014). Speed reduction between baseline conditions and with the  
401 ADAS was 0.40 km/h, however, this reduction was not statistically significant. The model  
402 estimation results revealed that the lateral clearance was influenced as well as the presence of  
403 the ADAS system, the various events, also the characteristics of the drivers such as: gender, the  
404 age, weekly driving frequency, and weekly cycling frequency.

405 The model estimation results revealed that accounting for possible heterogeneity in means and  
406 variances of the random parameters improves overall model fit and allows important new  
407 insights. What is likely happening is that the additional flexibility provided by mean/variance  
408 approach allows a more general structure for capturing unobserved heterogeneity relative to  
409 the standard approach (Behnood and Mannering, 2017).

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