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

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

1 INTRODUCTION

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

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

Cyclists are one of the most physically vulnerable road user groups, particularly when they share the road with motorized vehicular traffic. Their vulnerability as road users stems from their limited protection in the event of a collision and their low tolerance to the forces associated with collisions with motor vehicles. During a car accident involving a cycle, kinetic energy is transferred from the vehicle to the “unprotected” cyclist. Part of this energy will be 'absorbed' by the cyclist’ human body. When the amount of external forces exceeds the physical threshold tolerated by the human body, severe or fatal injury will occur. Weight (mass) and speed play a very prominent role in the released energy in the collision. When the collision speed increases, the amount of energy that is released increases as well. When a car and a bicycle collide, the difference in mass is huge and the collision energy is mainly absorbed by the lighter vehicle, so its occupants will have the greatest risk of serious injuries or even fatalities (Broughton, 2005; SafetyNet, 2007).

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

The passing manoeuvre is affected by a range of factors involving the cyclist, road configuration, traffic, and vehicle (Feng et al, 2018). To minimize risky car-cyclist interactions during overtaking, motorists try to choose safe and comfortable lateral distance from the cyclist, lateral clearance (LC). Several studies have highlighted the critical importance of the LC for objective and subjective safety while passing a cyclist (Rubie et al., 2020). However, although LC is definitely a key indicator of safety, an overtaking manoeuvre is a long and complex process which is not limited to the phase in which the vehicle moves parallel to the cycle, so the manoeuvre cannot be fully described by transient lateral clearance alone (Dozza et al., 2016).

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

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

In the context of ADAS systems, the human-machine interface (HMI) serves as a communication bridge between the vehicle and the driver and its optimal design play a decisive role to ensure the effectivity and the safety of such systems. The way the information is presented as well as the right timing are the two crucial factors for the design of a warning systems (Cao et al., 2009). A promising way to reduce transmission errors and enhance safety seems to be presenting information to drivers via multiple modalities, e.g. visual, auditory, or haptic warning (Schwarz and Fastenmeier, 2017). It can be assumed that different modalities should complement each other presenting one message (Cao et al., 2009). After receiving a warning message, drivers need certain amount of time for reacting and then performing appropriate actions to avoid the crash. Therefore, the delivery time of warning messages could seriously influence the effectiveness of the warning system (Yan et al., 2015). A warning presented too early might be interpreted by drivers as a false alarm and may eventually be ignored, leading to driver distraction or annoyance (Brown et al., 2001; Winkler et al., 2016). On the contrary, if the system warns drivers too late, there is not enough time for them to detect the warning, chose an avoidance response and take action to avoid or mitigate the collision. Compared to a single warning stage of imminent danger level, a multistage concept extends the warning range to more advanced cautionary levels of pre-warning or simply informing drivers about a safety–critical situation ahead. Thereby, a multistage warning can induce different driver reactions depending on the urgency level and the situation's intervention need with adapted intrusiveness. The early warning stages should be less intrusive as they might be triggered more frequently and would otherwise increase the probability of annoying drivers, whereas later warning stages certainly need a stronger salience to certainly elicit a driver reaction in an emergency (Winkler et al., 2016; Winkler et al., 2018).

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

2 EXPERIMENT

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

2.1 Car-cyclist overtaking ADAS system

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

(1) *Normal driving:* the driver is informed of the presence of a cyclist ahead at a safe lateral distance; no action is required by the driver;

(2) *Danger phase*: the driver is warned to an emerging risk situation which requires immediate attention and may require a corrective action;

(3) *Avoidable accident phase*: the driver is alerted to a critical situation which requires his/her immediate action or decision to avoid a potential crash.

The system alerts drivers using a combination of both visual and acoustic signals (Figure 1) positioned in a Head-up Display (HUD) projected on the vehicle's windshield. The visual information consists of a pictogram displaying front view symbols of a car and a cyclist separated by a double arrow which changes colour in each of the three warning phases and nudges the driver toward a corrective action. The normal driving condition is signaled only by a pictogram with green double arrow. The danger phase is introduced by an orange double arrow along with a beep sound to warn inattentive drivers. A red double arrow coupled with a high pitched double-beep sound is used to alert drivers in the avoidable accident phase.

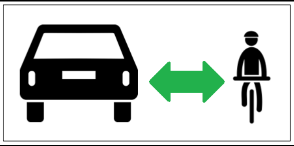
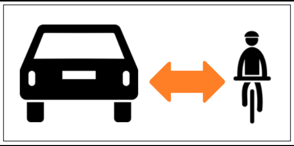
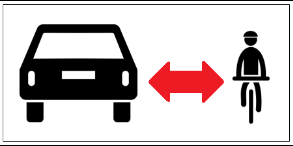
Phase / Signal	Normal driving	Danger phase	Avoidable accident phase
Visual			
Audio	No acoustic signal	Single Beep	Double high-pitched beep

Figure 1. ADAS warning phases

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

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

$$\mathrm{TTD} = \frac{Dist_{vh-c}}{\mathrm{Speed_{vh}} - \mathrm{Speed}_c} \quad (1)$$

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

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

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

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

Table 1. Warning criterion as combination of LC and TTD

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

2.2 Apparatus

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

2.3 Virtual road design

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

The experimental route consisted of 10 successive tangents with length equal to 1,000 m and 9 circular curves with 400 m radius and 35° deflection angle. The tangent-to-curve transition is carried out by spiral curves with a length equal to 55 m, which corresponds to 2.0 s at 100 km/h. The edge lines are continuous for the whole experimental road while the centre line is continuous from 150 m prior to 150m after each curve and dashed elsewhere. Speed limit signs of 70 km/h are posted at the start and repeated regularly along the experimental road. No separated/dedicated cycle lane was designed. Hence, motor vehicles had to share lanes with cyclists, interacting with each other. No symbols, signs or markings were installed on the road surface to advice the presence of cyclists on the road. The surroundings were modelled to mimic a real rural environment.

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

Event 1 | Event 2 | Event 3

Figure 2. Tested overtaking events during the experiment

2.4 Experimental procedure

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

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

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

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

2.5 Participants

Fifty participants took part in the study voluntarily, without any financial compensation. Two participants have been excluded from all further analysis (one due to an error in data logging, the other one because it was detected to be an outlier through the Grubbs test) leading to a sample size of 48 participants. No simulator sickness was observed. Moreover, the sample is composed of 21 women and 27 men, ranging in age from 19 to 66 years (mean = 32.44, standard deviation = 9.33). All the participants had a valid driving licence and at least 1 year of driving experience (mean = 11.94, standard deviation = 9.23). More than 60% of participants drive at least once a week, while about 30% occasionally drive . Participants rated their driving style on a scale of 1 (very defensive) to 5 (very offensive) (mean = 3.04, standard deviation = 0.90). More than 90% of the sample was aware of driver warning/assistance systems and about 40% had experienced at least once a driving aid system but, finally, only 25% use them frequently in their everyday driving.

Table 2. Driver characteristics: numerical variable

Numerical Variable	Mean	St. dev	Min	Max
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

Table 3. Driver characteristics

Categorical variable	Categories	#	%
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

Average annual kilometers travelled by car	0	3	6.25
	1 - 5000	17	35.42
	10001-20000	14	29.17
	5001-10000	9	18.75
	>30000	5	10.42
Weekly cycling frequency	Everyday	3	6.25
	2-4 times a week	15	31.25
	Every weekday	2	4.17
	Once a week	10	20.83
	Weekend only	3	6.25
	Never	15	31.25
Average annual kilometers travelled by bicycle	0	15	31.25
	1 - 50	19	39.58
	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

3 ANALYSIS METHODS

Lateral clearance and speed were used both as measure of driving behaviour during passing and as measure of effectiveness of ADAS system. The hypothesis of the study was that the presence of both cyclist and the ADAS system influences the risk perception, so that drivers react to such stimuli changing their driving style in the different overtaking events. Statistical tests and regression models with a random parameter were used to study the driver behaviour during car-bicycle overtaking and to evaluate the statistical significance of the experimental results.

3.1 Statistical test

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

3.2 Regression models with random effect

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

$$y_{it} = \beta_0 + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_p x_{pit} + v_{it} \tag{2}$$

y_{it} denotes the value of the dependent variable Y for individual i $(i = 1,..,N)$ at time point t $(t = 1, \dots, T)$, β_0 is the intercept, the β_p , $i = 0, 1, \dots, p$, are the regression coefficients, v_{it} is the error term which consists of two components $(v_{it} = u_i + e_{it})$, u_i "unobserved heterogeneity” component (individual specific but does not vary over time), and an e_{it} idiosyncratic component (varies across both individuals and time).

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

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

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

Since the observations are not independent of each other, residuals are not independent and, therefore, common likelihood-based methods and other measures of model fit from ordinary linear regression need to be adjusted (Pagliara and Mauriello, 2017). To get around this problem, a number of statisticians have developed so-called ‘Pseudo R^2 ’ measures that aim to mimic R^2 for logistic regression models. The most prominent one is McFadden’s Pseudo R2 is given by (Jobson, 2012):

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

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

4 RESULTS AND DISCUSSION

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

4.1 LC data

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

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]**	
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%

Table 5. LC: t and ANOVA tests

		A0			A1		
		E1	**E2**	**E3**	**E1**	**E2**	**E3**
	E1	1	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**0.014**
A0	**E2**		1	**<0.001**	**<0.001**	**<0.001**	**<0.001**
	E3			1	**<0.001**	0.499	**0.002**
	E1				1	**<0.001**	**<0.001**
A1	**E2**					1	**0.028**
	E3						1
ANOVA	F statistic = 69.907, df1 = 5, df2 = 858, **p-value = < 0.0001**						

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

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

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

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

Table 6. LC: random effects model

Variables	Coef.	Std. Err.	z	P>|z|	
ADAS					
A1	0.304	0.025	12.090	<0.001	***
A0					
Event					
E2	-0.650	0.031	-21.060	<0.001	***
E3	-0.444	0.031	-14.390	<0.001	***
E1					
Gender					
Male	0.111	0.037	2.98	0.003	**
Female					
Age	-0.012	0.0058	-2.09	0.037	**
Weekly driving frequency					
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					
Weekly cycling frequency					
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					
_cons	1.833	0.271	6.750	<0.001	***
σ_u	0.256	0.029			
σ_e	0.370	0.009			
ρ_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

The $\mathrm{McFadden} - R^2$ was equal to 0.36 (Table 7), and as reported by Anderson et al. (2013), this value indicated a very good of fit. This result was also confirmed by LR test performed comparing the fit at convergence model to the fit at constant model. LR test statistic likelihood ratio test between full and constant models ($LR_{\frac{\text{full model}}{\text{constant model}}}$= 479.14 with p-value <0.001) showed that the full random model fitted significantly better than the model with only constant. The value of the intra class correlation, ρ_0, evidenced that 32.3% of the variance was due to differences within drivers. The likelihood ratio test of σ_u= 0 was testing the null hypothesis that the standard deviation of the random intercept was equal to zero. The value of the likelihood ratio test of homoscedasticity ($LR\ test\ \sigma_u$= 0) was equal to 229.05 (p-value<0.001), highlighting the necessity to use random model.

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
$\mathrm{McFadden} - R^2$	0.362
$LR\ test\ of\ \sigma_u = 0$	229.05
Prob($LR2$, df=1)	<0.001
AIC	879.037
BIC	964.746

4.2 Speed data

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

Table 8. Mean and standard deviation of Speed

Event	A0 Mean Speed [hm/h]	A0 St. Dev. [hm/h]	A1 Mean Speed [hm/h]	A1 St. Dev. [hm/h]	$\frac{(\boldsymbol{Speed_{A1}} - \boldsymbol{Speed_{A0}})}{\boldsymbol{Speed_{A0}}}$
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 %

Table 9. Speed: t and ANOVA tests

		A0			**A1**		
		E1	**E2**	**E3**	**E1**	**E2**	**E3**
A0	E1	1	*0.067*	0.219	0.791	**0.026**	0.250
	E2		1	0.480	0.111	0.695	0.434
	E3			1	0.332	0.263	0.933
A1	E1				1	**0.047**	0.374
	E2					1	0.232
	E3						1
ANOVA	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

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

Table 10. Speed: Random effects model

Variables	Coef.	Std. Err.	z	P>|z|	
Event					
E2	-3.87204	0.846273	-4.58	<0.001	***
E3	-2.03919	1.363712	-1.5	0.135	
E1					
Gender					
Male	5.205	1.122	4.64	<0.001	***
Female					
_cons	70.118	6.223	11.27	<0.001	***
σ_u	12.784	1.351			
σ_e	10.155	0.251			
ρ_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

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
$\text{McFadden} - R^2$	0.003
$LR\ test\ of\ \sigma_u = 0$	657.97
Prob($LR\ test\ of\ \sigma_u$, df=1)	<0.001
AIC	7285.879
BIC	7304.925

5 CONCLUSION

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

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

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