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Article

Analysis of the Relationship Between Turning Signal Detection and Motorcycle Driver's Characteristics on Urban Roads. A Case Study

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Abstract: The relationships among the potential causes of a car and motorcycle collision involving turn maneuvers as well as the perception of rear and front turn signal (on/off) configuration is examined in this paper. The investigation has been based on data pooled from the answers of a survey proposed to 136 people, with special regards to the correct detection of indicators aspect. Experimental videos have been realized during the tests campaign, both in urban and suburban areas, using a 360-camera attached to a motorcyclist's helmet, reproducing vehicular conflicts able to potentially generate crash risks. The detection of the blinker was combined with other factors (e.g. age, gender, location of the test site, presence of the car behind tester vehicles and if the bikers are also habitual car or bike drivers) in a stepwise logistic regression that modelled the odds of detecting the turn signal turned on as a function of all of these factors. The results suggest the existence of a connection between the detection of the turn signal aspect and some of the variables considered (e.g. age, being a cyclist or a car driver and the presence of a protecting car).

Keywords: motorcycle crash risk; intersection; vehicle turning signals; conspicuity; Logit model

1. Introduction

Crashes related to powered two wheelers are well known to be documented as the origin of most of the unnatural death worldwide. Nearly half of all fatalities on the world's road infrastructures are among the ones with the lowest level of protection (i.e. motorcyclists, pedestrians, and cyclists). Specifically, motorcyclists represented 10% of road deaths in Europe, 20% in America, and 34% in Asia states [1].

In Europe, according to stats [2, 3], eleven bike drivers or passengers are killed per 100,000 registered motorcycles. More than a half more compared with just five per same quantity of registered cars. The share of powered two wheelers riders' fatalities among all road deaths differs throughout the Europe states, from 5% in the Balkan states to 35% in Greece. From 2011 to 2016 the amount of accidents occurrence and motorcyclists killed or injured in Italy is slightly diminished. Moreover, the number of casualties was 205,747 in 2011; this had reduced to 175,792 in 2016 [5]. From that same year, the number of casualties has kept on following a descending pattern.

Other than the higher demise rate, motorcyclists are more likely to get injured when involved in an accident [6]. Horswill and Helman [4] dug into 403 injury accidents in the UK in which either a bike or car was part of a head on impact with a vehicle. About 97% of powered two wheelers riders were hurt or killed in these accidents compared with 51% of car drivers. Since there is a higher likelihood that motorcycle-car collisions can occur at higher velocities than the ones between two cars, they analysed a sample comprised of 111 motorcycle-car head on accidents, chosen from the previous dataset, and found out that the riders involved had a 96% to get injured compared to just the 1% of car drivers. This big difference seems to confirm that motorcyclists are much more vulnerable than car drivers.

1.1. Literature on motorcycles crash

Motorcycle accident researches give adequate proof that it is fairly difficult for the car drivers seeing motorcyclists, especially when traffic flow is high and consequently the visual field is crowded of vehicles. A typical claim of vehicle drivers involved in accidents is that they did not detect the motorbikes and their riders in time or did not notice them by any means.

Generally, half of the times in which a vehicle driver neglected to distinguish a bike so as to get away from a probable crash, many obstacles were present in the surroundings scenes, causing an interference of the driver's line of sight. The capability of other drivers to detect the motorcycle is named 'conspicuity'. Usually power two wheelers are smaller than cars or trucks, then it is much harder to detect them, since also their approaching speed is more difficult to estimate quantitively. This contributes to a great extent to the large number of motorcycles accidents. Hancock et al. [7] and Wertheim [8] defined two leading factors causing the drivers failing to see bikers: sensory conspicuity (i.e. motorcycles have a small size) and cognitive conspicuity (i.e. motorbikes are less frequent and hence less expected than other modes of transport). Size, as mentioned, is one of the important factors influencing conspicuity. The frontal area is one third of a passenger car, although it might differ changing the angle of the configuration. It should be considered that under daytime surrounding conditions, even bikes are able to be seen and avoided in case of an imminent impact when entering in a driver's visual field. In any case, the small size of the motorcycles increases the probability that they fit in with every other vehicle present on the streets and their detection rely just on the ability of being able to be seen in the gap between cars. Furthermore, individuals detect objects considering their color, size, shape and kinematic parameters. From far away, motorbikes remind to pedestrians or bicycles, aside from their velocity. Since the conspicuity physical characteristics of a motorcycle are related to the judgment of speed, many times drivers are unable to see them from a distance.

Aggressive driving could be deemed as an additional cause to the occurrence of motorcycle crashes. Not only the attitude of driving but also the fact that drivers usually are more prone to accept risk (e.g. alcohol assumption [9]). Risky driving behavior has been identified as the input of the occurrence of numerous vehicle accidents [10]. Horswill and Helman [4] investigated the motorcyclists conduct while driving and found out that they used to travel at higher speed than cars, overtook more and drive through the small gaps between the other vehicles during rush hours.

Demographic factors play a big role in the risk-taking behavior of motorcyclists. For instance, various investigations [11-14] found that younger bikers have higher probabilities of getting involved in a road accident. Young male riders drive more dangerously than women and older road users and have lower likelihoods of detecting hazards [16]. Furthermore, it appears that bikers who see an imminent high-risk event do not embrace precaution actions in order to avoid it, even if they have already experienced a similar situation [17-18].

As indicated by few investigation [19-21], there are some distinctive characteristics of motorcycles that make the bikers increasingly inclined to injuries and crashes. First of all, motorcycles usually have higher horsepower row height ratio than cars at a much lower price, making them very affordable for almost everyone. Likewise, being a one-track vehicle, the instability of equilibrium is much more likely to happen compared to cars, especially while braking or on slippery road surfaces.

Longitudinal irregularities or cutting of the road surface, and raised zebra crossing, may be the cause to instability condition for the bikes. Further causes of crashes could be the incorrect use of brakes. One crucial representative of a motorcycle is to be a balanced machine. Thus, the improper actuation of the brakes may lead to overturn and skidding conditions. An investigation by Sheppard et al. [22] studied the use of motorcycle brakes by observing the bikers' behavior at road intersection. In normal conditions, more than 30 % of the riders used just the rear brake while just 10 % utilized only the front brake [23].

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1.2. Literature on turn signals

Even though vehicle turn signals advanced and progressed toward become standardized over the course of the last century, many differences emerged between U.S. and European guidelines. The specific distinction between the two guidelines is that Europe requires tail turn signal to be solely yellow, while in the U.S. they can be either yellow or red.

Hence, in Europe all tail turn signals emit a yellow light, while in the U.S. they can be colored either amber or red. The reason for this choice lies behind the decision made by the Group de Travail-Bruxelles at an event in 1960. The GTB prescribed the use of amber turn signal to the Europeans and the Americans. In the meantime, United States makers dismissed the exclusive use of amber turn signal in favor of red turn lights, basing their decision on doubtful money saving advantages [24].

In general terms, the exclusive use of amber rear turn signal condition would be preferred to the situation in which either a yellow or red light can be used. That is because of human being perception level: a yellow turn signal would be more effectively recognized from other reddish colored turn lights by the difference in color with brake lights for example [25]. In addition, current light technology requires the utilization of discrete lights compartments for the different colored lamps, guaranteeing that amber turn lights are spatially separated by the red brake lights [26]. Lamp separation helps to better distinguish the contrast between the on and off state of the light.

Consistency throughout the globe is the key word to increase the probability of easily detect the turn signal light [27-28]. There have been a couple researches inspecting the potential of permitting two different colored turn lights. Luoma et al. [29] noticed that the response time to a braking signal is shorter in the case of yellow turn signal compared to the red one. In any case, it must be considered that the study was performed outside the U.S., where the presence of both the amber and the red turn signal could have given mixed results [30-32]. Braitman et al. [33] pointed out another aspect contributing to crashes: the age. In fact, the number of accidents increases when older people drive, usually at the intersection while turning left.

As cited before, utilization of yellow turn lights requires separation from tail stop lights giving both a spatial offset between the tail lights and a boost to the contrast between on and off state.

These are the different studies we found on the matter of turn signal detection. Similarly, our study is focused on the detection of turn signal, but more on the rate of detection rather than the type of color.

2. Materials and Methods

As already mentioned, the research question lying at the basis of this study is to determine whether the turn signal has a big impact on the sight of motorcyclists in specific riding situations, or is something not that important. To try to answer this question, many tests have been designed and performed, recording videos shot by a helmet's camera (plus the internal view ones). In the survey phase, a virtual reality visor has been used to allow individuals of a selected sample to watch videos and, finally, respond to a questionnaire. Wrapping up, these are the tools used throughout the study:

- Samsung gear 360 camera;
- Samsung gear VR visor;
- GoPro hero 3;
- Samsung galaxy s7 G-930F;
- Action Director Software;

(a) (b) (c)

Figure 1. Samsung gear 360 camera **(a)**; Samsung Gear VR produced by Oculus **(b)** and GoPro Hero 4 attached to a helmet **(c)**.

The 360 camera is able to capture 360-degree videos and photos; it has been mounted on motorcyclist's helmet and controlled via smartphone, as described in the following. The Samsung Gear VR powered by Oculus (i.e. Gear VR) is a head mounted, virtual reality device which allows the interviewed people to watch the videos realized during the tests in an immersive and realistic way. Finally, the GoPro Hero is the camera that will be mounted on side of the head of the car driver to show the turning signal of the motorcycle approaching the car. On the front panel, a f/2.8 six-element aspherical lens that is supposed to reduce the amount of barrel distortion is installed.

2.1. In-situ tests

The tests consist of capturing videos showing a motorcycle (vehicle A) driving on an urban road (first three tests) and a suburban road (last three test). Two cars (vehicle B and C, respectively) are placed steady at the intersection of the two roads (see fig. 2). The first set of videos will be shot through the camera attached on the motorcyclist helmet. Contemporarily, videos inside the car stopped at the intersection will be shot using the GoPro Hero attached to the driver's head.
The test foreseen the use of three vehicles, a motorbike and two sedan cars. The motorbike is identified as "Vehicle A". The cars are identified as "Vehicle B" and "C", respectively. The vehicle C assumes the role of protecting vehicle: it partially prevents the sight of the arriving motorcyclist seeing the blinker of the vehicle B.

(a) (b)

Figure 2. Test-site intersections, located in urban area (a) and in suburban area (b). (Coordinates *44°32'07.0"N 11°21'33.6"E* for urban intersection and *44°31'38.2"N 11°23'38.0"E* for suburban intersection)

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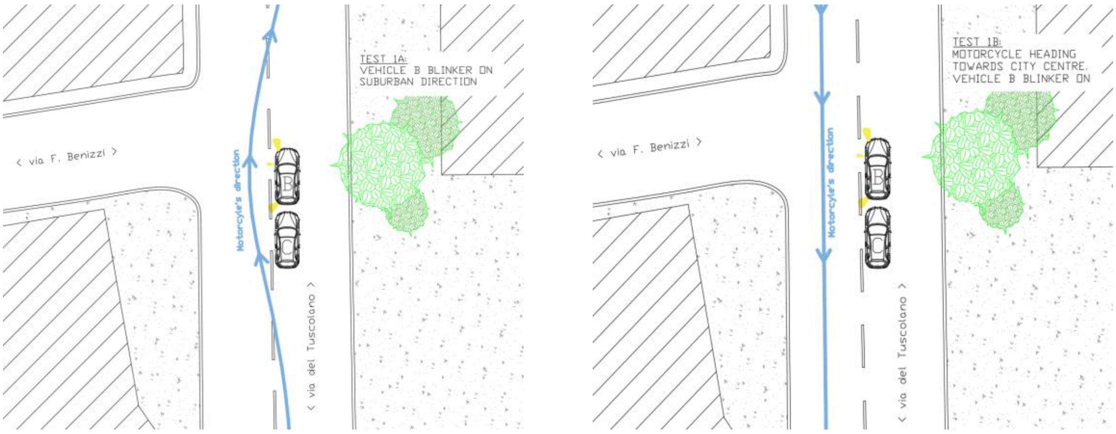
2.1.1. Test 1 (urban intersection)

The first test comprised two phases, a and b (see fig. 3):

a) The vehicle B is stationary at intersection with the turning signal ON (in preselection position). The vehicle C is stationary at intersection, behind the vehicle B, with the turning signal OFF. The motorcycle (vehicle A) drives (~ 50 km/h) along the main road heading from city centre towards suburbs area and during the overtaking of the two vehicles B and C the blinker of the bike will be turned ON.

b) The motorcyclist, after the roundabout has been entirely travelled, will push the horn to signalize the beginning of the second part of the test. The motorcycle (vehicle A) drives (~ 50 km/h) along the main road heading from suburbs areas towards city centre. The vehicle B has the turning signal ON. The vehicle C is in the same position as the test 1a.



(**a**) (**b**)

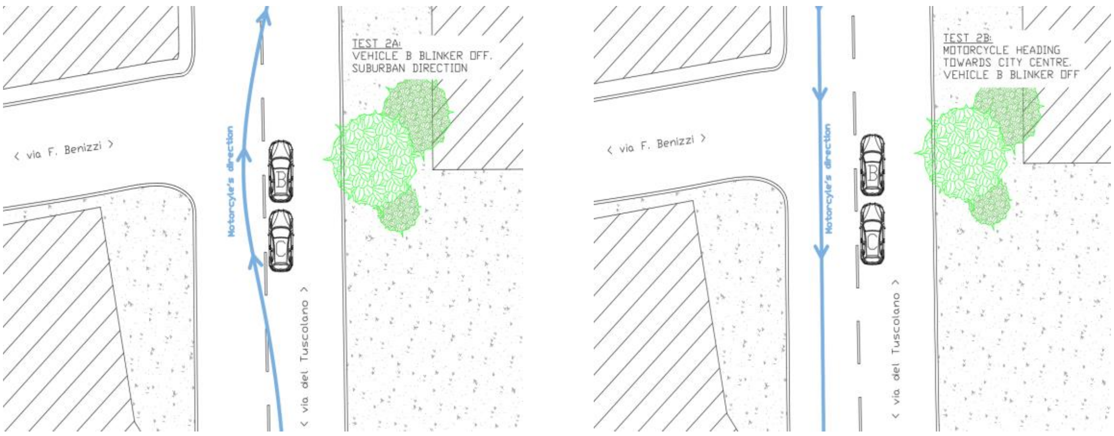
Figure 3. Test 1(a) and 1(b) schemes.

2.1.2. Test 2 (urban intersection)

The second test also included two phases, a and b (see fig. 4):

a) The vehicle B is stationary at intersection 1 with the turning signal OFF (in preselection position). The vehicle C is stationary at intersection 1, behind the vehicle B, with the turning signal OFF. The motorcycle (vehicle A) drives (~ 50 km/h) along the main road heading from city centre towards suburbs area and during the overtaking of the two vehicles B and C the blinker of the bike is OFF.

b) The motorcyclist, after the roundabout has been entirely travelled, will push the horn to signalize the beginning of the second part of the test. The motorcycle (vehicle A) drives (~ 50 km/h) along the main road heading from suburbs areas towards city centre. The vehicle B has the turning signal OFF. The vehicle C is in the same position as the test 2a.



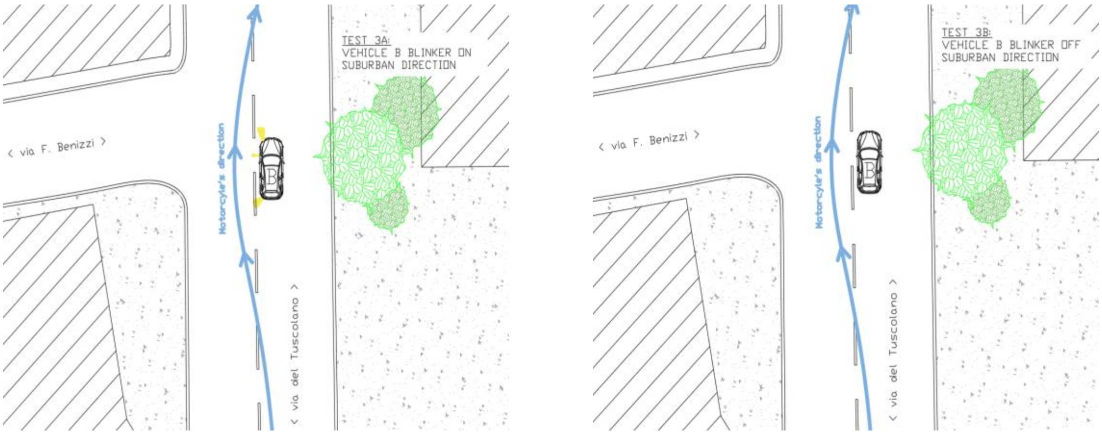
(**a**) (**b**)

Figure 4. Test 2(a) and 2(b) schemes.

2.1.3. Test 3 (urban intersection)

The third test is characterized by the fact that the vehicle C is not used. There are two phases, both in suburbs direction (see fig. 5):

a) The vehicle B is stationary at intersection 1 with the turning signal ON. The motorcycle (vehicle A) drives (~ 50 km/h) along the main road heading from city centre towards suburbs area and during the overtaking of the vehicle B the blinker of the bike is ON.
b) The vehicle B is stationary at intersection 1 with the turning signal OFF. The motorcycle (vehicle A) drives (~ 50 km/h) along the main road heading from city centre towards suburbs area and during the overtaking of the vehicle B the blinker of the bike is OFF



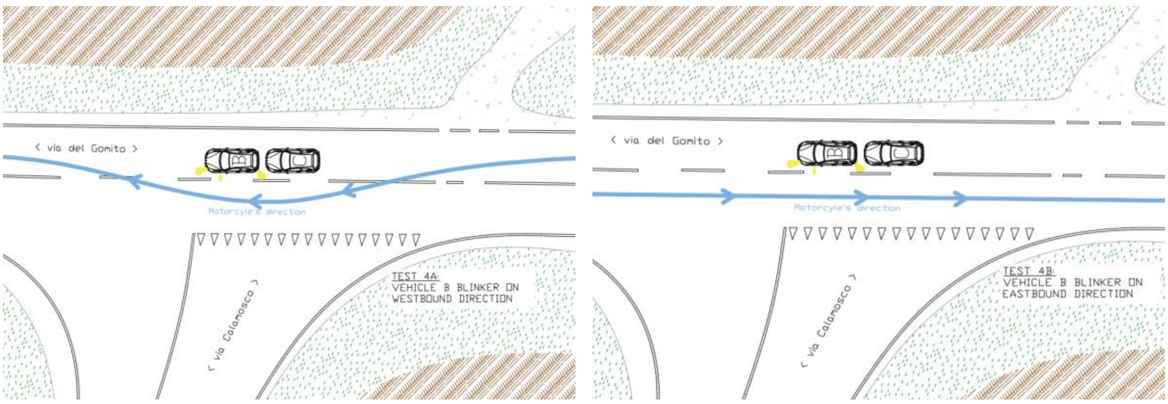
(**a**) (**b**)

Figure 5. Test 3(a) and 3(b) schemes.

2.1.4. Test 4 (suburban intersection)

The forth test comprised two phases, a and b (see fig. 6):

a) The vehicle B is stationary at intersection 1 with the turning signal ON (in preselection position). The vehicle C is stationary at intersection 1, behind the vehicle B, with the turning signal OFF. The motorcycle (vehicle A) drives (~ 50 km/h) along the main road heading westbound and during the overtaking of the two vehicles B and C the blinker of the bike will be turned ON.
b) The motorcyclist, after a U turn, will push the horn to signalize the beginning of the second part of the test. The motorcycle (vehicle A) drives (~ 50 km/h) along the main road heading eastbound direction. The vehicle B has the turning signal ON. The vehicle C is in the same position as in the test 4a.



(**a**) (**b**)

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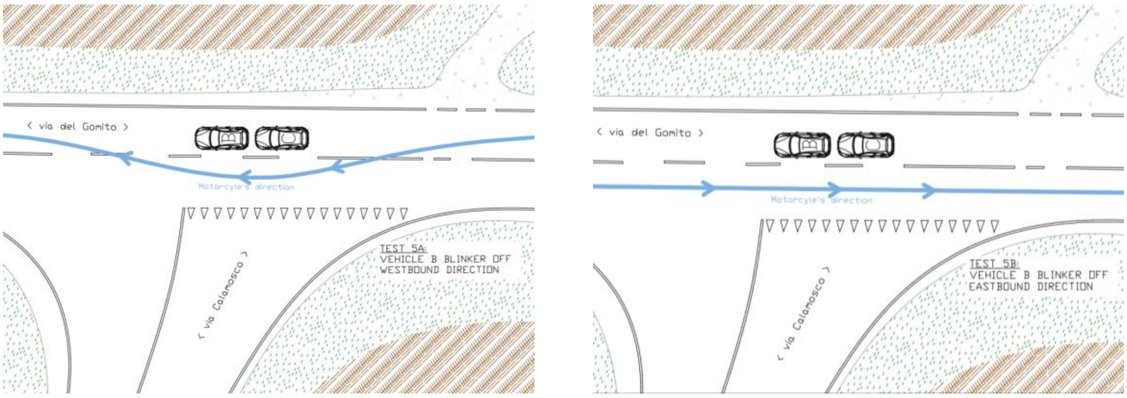
Figure 6. Test 4(a) and 4(b) schemes.

2.1.5. Test 5 (suburban intersection)

The fifth test is, again, comprised two phases a and b (see fig. 7):

a) The vehicle B is stationary at intersection 1 with the turning signal OFF (in preselection position). The vehicle C is stationary at intersection 1, behind the vehicle B, with the turning signal OFF. The motorcycle (vehicle A) drives (~ 50 km/h) along the main road heading westbound and during the overtaking of the two vehicles B and C the blinker of the bike is OFF.
b) The motorcyclist, after a U turn, will push the horn to signalize the beginning of the second part of the test. The motorcycle (vehicle A) drives (~ 50 km/h) along the main road heading eastbound. The vehicle B has the turning signal OFF. The vehicle C is in the same position as in the test 2a.



(**a**) (**b**)

Figure 7. Test 5(a) and 5(b) schemes.

2.2. Survey design and data collection

The videos collected from the 360-camera during the tests have been edited and rendered in the ten videos representing the base for the survey. In order to do so, the editing software "action director" designed and developed by Samsung has been used. For each test, the images were treated with cutting and editing procedures (fig. 8), obtaining the final ten videos to be used for the survey phase.

Figure 8. Video editing procedure.

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In the producing phase the resolution of 2880x1440 pixel and 24 frames per seconds has been selected. This is because the smartphone's display resolution is the same of the video (and the refresh rate too).

During the survey phase, a sample of 136 users (the characteristics of which will be illustrated in par. 3.1) watched the previously edited videos using the Samsung Gear VR, and then answered the questions of a questionnaire specifically designed, giving information regarding the aspect of the turning indicator as detected by the interviewed person and other relevant variables (age, gender, being habitual car or bike driver).

2.3. Data analysis – logistic regression model

Regression methods have gradually become a fundamental aspect of data analysis related to the relationship between a response variable (e.g. occurrence of road accidents) and one or more independent variables (i.e. influencing factors). In literature is widely recognized [34-35] that the utilization of conventional regression analysis is unsuitable to identify probabilistic issues concerning the occurrence of road accidents and to investigate the relationship among crash rate and factors that can influence it. Since the end of the last century, logistic regression has been widely applied to develop accident models and to study crash outcome [36-38].

In statistics, logistic regression or logit regression is a type of probabilistic model. The key mathematical idea that underlies logistic regression is the logit, the natural logarithm of an odds ratio. Often, logistic regression is utilized referring to the problem in which the dependent variable is binary (there are two available categories and problems with more than two groups are known as multinomial logistic regression). It is also used to foresee a binary response from a discrete or binary predictor [39]. The probabilities describing the possible outcomes of a single test are modelled, as a function of the attribute's variables, using a logistic function. A least square test is used to show how good the logistic regression model fits the dataset.

More in detail, a binary output variable Y is given, and the conditional probability Pr (Y = 1|X = x) = E(Y/X) is exhibited as a function of x (*p(x)*); any unknown parameter in the function can be estimated by the concept of maximum likelihood. The easiest modification of ln *p(x)* is the logistic transformation (i.e. logit), $ln\frac{p}{1-p}$.

Formally, the logistic regression model is:

$$ln\frac{p(x)}{1-p(x)} = \beta_0 + x \cdot \beta \tag{1}$$

Solving for p(x) gives:

$$p(x) = \frac{e^{\beta_0+x\cdot\beta}}{1+e^{-(\beta_0+x\cdot\beta)}} \tag{2}$$

As logistic regression give as output probabilities, rather than just classes, we can fit it using likelihood. For each component of the dataset, we have a vector of attributes, x_i, and an observed class, y_i. The occurence of that class is either $p(x)$, if $y_i = 1$, or $1 - p(x)$, if $y_i = 0$. The likelihood function is given by:

$$\ell(\beta_o, \beta) = \prod_{i=1}^{n} p(x_i)^{y_i} \left(1 - p(x_i)\right)^{1-y_i} \tag{3}$$

Typically, to find the maximum probability values – and so to find the unknown values of the parameters that maximize the probability to observe the values given by the model – it is necessary to differentiate the log probability with respect to the parameters, and solve the derivates for zeros. To do that, take the derivative of (3) with respect to one element of β, say β_j.

$$\frac{\partial\ell}{\partial\beta_j} = -\sum_{i=1}^{n}\frac{1}{1+e^{\beta_0+x_i\cdot\beta}}e^{\beta_o+x_i\cdot\beta}\cdot x_{ij} + \sum_{i=1}^{n} y_i x_{ij} = \sum_{i=1}^{n}(y_i - p(x_i;\beta_o,\beta))\cdot x_{ij} \tag{4}$$

Eqn. (4) cannot been solved exactly, usually it can be treated with numerical optimization methods.

3. Results

3.1. Description of the variables

In table 1 the characteristics of the sample and the variables considered in the analysis are reported. In particular, the sample is uniform concerning gender (43% male), habitual cycle drivers (almost 50%) and the tests have been performed balancing the presence of protecting car and the urban or sub-urban environment.

Table 1. Description of the study variables

Description	Values	Count (proportion)	Name
Correct detection	0 = no	82 (60%)	SIG
	1 = yes	54 (40%)	
Cyclist	0 = no	70 (51%)	CYC
	1 = yes	66 (49%)	
Car Driver	0 = no	44 (32%)	CAR
	1 = yes	92 (68%)	
Gender	0 = male	58 (43%)	GEN
	1=female	78 (57%)	
Age	0 = if ≥ 50	35 (26%)	AGE
	1 = if < 50	101 (74%)	
Protection	0 = no	68 (50%)	PROT
	1 = yes	68 (50%)	
Urban	0 = no	68 (50%)	URB
	1 = yes	68 (50%)	

The sample is mainly composed by habitual car drivers (68%) and, finally, regarding the age, most of the sample is under the age of 50 (74%).

3.2. Model estimation

As reported in section 2.3 a logistic regression model has been specified and calibrated, basing on the results of the performed survey. Table2 shows the results from fitting all the explanatory variables simultaneously. From the Wald statistic values, it appears that the variables CYC, CAR, AGE and PROT show significant effect at 5% level.

Table 2. Estimated coefficients, estimated standard errors, *p*-values and Wald statistic for the model variables

Variable	Coefficient	Std. Err.	Wald statistic	P-value
Intercept	-3.320	0.906	13.4	<0.001*
CYC	-1.049	0.449	5.46	0.019*
CAR	1.203	0.569	4.46	0.034*
GEN	0.091	0.455	0.039	0.841
AGE	2.171	0.630	11.86	<0.001*
PROT	0.747	0.368	4.13	0.042*
URB	0.209	0.386	0.294	0.587

* Statistically significant at 5% level.

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Hence, the logistic regression model calibrated in this study is:

$$p(x) = \frac{e^{-3.320-1.049\cdot CYC+1.203\cdot CAR+2.171\cdot AGE+0.747\cdot PROT}}{1+e^{-3.320-1.049\cdot CYC+1.203\cdot CAR+2.171\cdot AGE+0.747\cdot PROT}}$$

Where $p(x)$ is the conditional probability to correctly detect the car turning indicator in the tested context. The logit of the logistic regression model is given by:

$$ln\frac{p(x)}{1-p(x)} = -3.320 - 1.049\cdot CYC + 1.203\cdot CAR + 2.171\cdot AGE + 0.747\cdot PROT$$

The fit of the model has been tested considering the log-likelihood statistics:

$$2(LL_1 - LL_0) = (-2LL_0) - (-2LL_1) \sim \chi^2$$

Where LL_1 is the log-likelihood of the full model, and LL_0 is the log-likelihood of the reduced model (in particular, the model running with only the intercept). The degrees of freedom (*df*) of the chi-square variable are the number of variables considered in the full model minus the number of parameters in the reduced model. The computed values for the estimated model are:
LL_1 = -78.70
LL_0 = -91.39
p-value < 0.001 → the model is significant.

4. Model interpretation and discussion

Both main effects and interactions among parameters and the conditional probability to detect the turning indicator can be evaluated considering the model coefficients β_k, which directly allows to calculate odds ratio involved in turning signal detection. The odds of a given event are generally defined as the probability of the event occurring divided by the probability of the event not occurring. More in detail, the interpretation of the actual effect of a coefficient in a logistic regression model and its magnitude depends on the possibility to explain and interpret the difference between two logits. The exponent of this difference gives again the odds ratio, which is defined more in detail as the ratio of the odds that the variable examined will be cause to the odds that it will not be cause. All the estimated odds ratios are reported in tab. 3 and in the following sub-paragraphs a brief description of the effects of significant parameters is given.

Table 3. Effects of the estimated coefficients on the probability *p(x)*

Variable	Coefficient	Odds ratio	Effect
CYC	-1.049	0.35	Negative
CAR	1.203	3.33	Positive
AGE (< 50)	2.171	8.77	Positive
PROT	0.747	2.11	Positive

4.1. Impact of being habitual cyclist on turning signal detection

The estimated coefficient of the parameter CYC, according to tab. 2, is -1.049; to interpret the effect of this parameter the logit difference can be evaluated as follows:

Logit (sign detect / habit cyc) = $-3.320 - 1.049\cdot CYC + 1.203\cdot CAR + 2.171\cdot AGE + 0.747\cdot PROT$
Logit (sign detect / non - habit cyc) = $-3.320 + 1.203\cdot CAR + 2.171\cdot AGE + 0.747\cdot PROT$
Logit difference = $-1.049\cdot CYC$

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The odds ratio is: $OddsR = e^{-1.049} = 0.35$, meaning that being habitual cyclist seems to reduce the probability of detecting the turning signal by a factor of 0.35.

4.2. Impact of being a habitual car driver on turning signal detection

The estimated coefficient of the parameter CAR, according to tab. 2, is 1.203; the logit difference in this case is:

Logit (sign detect / habit car driver) = $-3.320 - 1.049 \cdot CYC + 1.203 \cdot CAR + 2.171 \cdot AGE + 0.747 \cdot PROT$
Logit (sign detect / non - habit car driver) = $-3.320 - 1.049 \cdot CYC + 2.171 \cdot AGE + 0.747 \cdot PROT$
Logit difference = $1.203 \cdot CAR$

The odds ratio is, finally: $OddsR = e^{1.203} = 3.33$ meaning that the odds of detecting the turning signals being a habitual car driver are 3.33 times higher than those for non – habitual car drivers.

4.3. Impact of age on turning signal detection

The estimated coefficient of the parameter AGE, according to tab. 2, is 2.171; this variable has to be treated carefully, because, as previously described, the age of the people in the sample is not uniformly distributed. The association between driver's age and involvement in road accidents is well known and investigated in the literature for both four wheels (see for example [40]) and two wheelers vehicles [41]. In particular, it has been shown that younger motorcyclists have a higher propensity for risky behaviors and these behaviors have been shown to be associated with increased risks of accidents [18]. At the same time, it is widely recognized that elderly drivers are at particular risk for vehicle crashes in challenging driving environments; this is mainly due to age-related visual, cognitive and physical dysfunctions [33, 42].

The logit difference, evaluated as follows, confirms these last considerations:

Logit (sign detect / age < 50) = $-3.320 - 1.049 \cdot CYC + 1.203 \cdot CAR + 2.171 \cdot AGE + 0.747 \cdot PROT$
Logit (sign detect / age ≥ 50) = $-3.320 - 1.049 \cdot CYC + 1.203 \cdot CAR + 0.747 \cdot PROT$
Logit difference = $8.77 \cdot AGE$

The odds ratio is, finally: $OddsR = e^{2.171} = 8.77$ meaning that the odds of detecting the turning signals for drivers with age < 50 are 8.77 times higher than those for older drivers.

4.4. Impact of presence of a protection car on turning signal detection

The estimated coefficient of the parameter PROT, according to tab. 2, is 0.747; to interpret the effect of this parameter the logit difference can be evaluated as follows:

Logit (sign detect / presence of prot car) = $-3.320 - 1.049 \cdot CYC + 1.203 \cdot CAR + 2.171 \cdot AGE + 0.747 \cdot PROT$
Logit (sign detect / assence of prot car) = $-3.320 - 1.049 \cdot CYC + 1.203 \cdot CAR + 2.171 \cdot AGE$
Logit difference = $0.747 \cdot PROT$

The odds ratio is, finally: $OddsR = e^{0.747} = 2.11$ meaning that the odds of detecting the turning signal in the presence of a protecting car are 2.11times higher than the situation in which the car is not present.

5. Conclusions

In this work, the description of an experimental research design finalized to explore the possible determinants of car turn signal (blinkers) detection by motorcyclists is presented. The analyses have been performed realizing some videos during tests campaign, both in urban and suburban areas, using a 360-camera attached to a motorcyclist's helmet. The tests have been set to reproduce vehicular maneuvers (i.e. left turn in 3-leg road intersections) able to potentially generate crash risks. The videos have been edited and rendered, realizing the base for the survey consisting in a questionnaire specifically designed and subjected to a sample of 136 users. The detection of the blinkers (turning indicators) was combined with other factors (e.g. age, gender, location of the test site, presence of the car behind the tester vehicle and if the bikers are also habitual car or bike drivers) in a stepwise logistic regression that modelled the odds of detecting the turn signal turned on as a function of all of these factors.

Within the limits of any regression analysis, relationships seem to exist between the considered attributes and the odds of turn signal detection by motorcyclists. First of all, gender and urban context do not seem to have a statistically significant influence on the perception of turning indicator. Moreover, being a habitual cyclist seems to have a negative influence on the perception of the turn indicator, although slightly. Habitual car drivers have significantly higher chances of detecting the turning signal, probably due the usual conditions that drivers typically face on a roadway. Testers age plays a big role in the signal detection, as younger users have higher detection rate compared to older people. Finally, the presence of the protecting car leads to higher detection rate of the blinker. This could be associated to the fact that an additional car behind the test vehicle is perceived as a higher risk situation, which increase the user's awareness. The latter is probably the most interesting result of our analysis, as many accidents occur, in urban contexts, in such conditions.

Turn signal detection is a problem not only related to distracted drivers, but also to various environmental and driving conditions and it should be further investigated in order to mitigate the risk of accidents. As the main goal of the stakeholders involved in research and industrial development on road safety is to significantly reduce injuries, deaths and property damage, the preliminary results of this study show that we should take a serious collective look at the subject of turn signal detection and strive to proactively improve it so that all drivers appropriately perceive the blinker at all times.

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