Prospective Evaluation of Autonomous Emergency Braking systems Performance in Car-to-Powered Two-Wheelers Accidents in France.

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Abstract Autonomous Emergency Braking systems with Powered Two-Wheelers (PTW) detection (AEB- PTW) are expected to equip vehicles in the near future. This study aims at prospectively estimating the performance of AEB-PTW in avoiding accidents or mitigating their consequences, based on real-world, representative car-to-PTW French accident data. The same accidents were re-simulated using kinematic models of the vehicles, ideal AEB-PTW sensor models and realistic detection-action logics. The effectiveness of AEB-PTW could then be assessed in terms of reduction in fatal, severe, and slight injuries, using injury risk curves that were built from the same accidents sample. Performance results showed that fitting AEB-PTW on cars could potentially lead to halving the most severe PTW users' casualties in crossing and left turn across path configurations. AEB-PTW performance in car-PTW rear-end accidents was even higher, reaching up to a potential 80% reduction of the most severe casualties. This performance is obtained at the expense of a steep upgrade of AEB sensor settings as compared, for example, to AEB-Pedestrian. To the authors' knowledge, this is the first attempt at assessing the potential effectiveness of AEB-PTW systems, based on representative accident data, for all levels of injury.

Keywords Autonomous Emergency Braking (AEB), Powered Two-Wheelers (PTW), car-to-motorcycle accidents, effectiveness, injury risk curves.

I. INTRODUCTION

According to data based on observations extending up to 2016 [1], depending on country, 28% of the 1.35 million persons killed annually on the road are riders of powered two or three-wheelers (approximately 378,000 persons killed). Southeast Asia, West-Pacific and South America are the most critical areas, with respective proportions of 43%, 36% and 30% of powered two-wheelers (PTW) users among road fatalities.

In 2019, in European countries, PTW users accounted for 18% (4,166 persons) of road fatalities, of which 45% (1,865 persons) were killed in a collision with a passenger car [2]. In France, 749 PTW users were killed in 2019, 269 of them against a passenger car [3].

To increase vulnerable road users' safety, one solution is to fit cars with Advanced Driver Assistance Systems (ADAS). Autonomous Emergency Braking (AEB) is one of these and it can either avoid crashes or mitigate their consequences, by automatically applying the vehicle brakes. Depending on technical definition, the system may warn the driver and only apply the brakes if he/she is unresponsive.

The scientific literature contains several studies prospectively addressing AEB-pedestrian effectiveness [4-6] with first retrospective studies emerging [7] as the market penetration of AEB technology increases. Only few studies prospectively addressing AEB-cyclist effectiveness [8-9] with the help of injury-risk curves, and one retrospective study [10] could be found without statistical significance of results due to low market penetration of AEB equipped vehicles, which resulted in a small sample of car-to-cyclist accidents involving these vehicles. In contrast with the magnitude of the problem, only a handful of studies in connection with AEB effectiveness in addressing car-to-PTW crashes have been published to date, to the best of the authors' knowledge: deducing AEB-PTW potential effectiveness was attempted by supposing same effectiveness levels as car-to-car AEB in the same accident configurations [11]. Setting up injury risk curves for a more complete assessment was separately attempted in another study [12].

In this study, injury risk curves were derived from representative French accident data [13]. Various parameters were tested as inputs for a set of two regression models. The model that best fits our data was used

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in the assessment of the AEB technology's effectiveness in avoiding or mitigating the effects of car-to-PTW collisions after re-simulating the accidents with ideal AEB-PTW sensor models and realistic detection-action logics. This methodology was applied on the following accident configurations focusing on the most likely AEB- PTW use cases to be tested by European New Car Assessment Programme (Euro NCAP) in the upcoming protocols: Straight Crossing Path at intersections (SCP); Left Turn Across Path by car with PTW in Oncoming Direction (LTAP/OD); Rear-End by car.

II. METHODS

VOIESUR accident database

As was the case in previous studies [6][9], French accident database VOIESUR was used in the present study for the selection of car-to-PTW accidents. This database was built in the context of the VOIESUR project that was set up in 2012 and was partly funded by the French National Research Agency (ANR) and involved four major actors of road safety research in France (LAB, CEREMA, IFSTTAR, and CEESAR). VOIESUR database resulted from the analysis of more than 8,500 police reports from 2011 in France, which included all fatal accidents and 5% of all injury accidents for that year. Based on photos, maps, medical information, and interviews available in the reports, accident experts added information related to vehicles, e.g., vehicle type, registration year, environment, e.g., infrastructure type, weather conditions, collisions, e.g., impact speed, collision deformation classification, human functional failure, e.g., detection, diagnostic, decision, types and explanatory elements.

In order to compute the impact speed of each vehicle and subsequently closing speeds, accidents have been reconstructed using a well-known methodology in accident science [14].This methodology is based on the kinetic energy and linear momentum conservation laws, as well as dividing the accident scenario into various phases for each participant, beginning from pre-crash into final position of each vehicle after collision. With the help of photos of the implicated vehicles and scaled maps of the accident scene included in VOIESUR accident reports, the necessary input parameters for the reconstruction methodology were estimated. Some examples of such parameters are the vehicles weight, the angles just before and just after collision, the distance travelled by each vehicle after collision, the equivalent energy speed (EES) based on vehicle deformation, etc. Some hypotheses about deceleration before and after impact were made, based on surface material (asphalt, gravel, etc.) and surface condition (dry, wet, etc.). A tool was developed to enable experts to compute speeds out of these parameters. Consequently, the speeds were coded in VOIESUR database. However, the tool did not enable the estimation of speed error propagation due to possible measurement errors of the input parameters.

Not only VOIESUR is a detailed database but it is also representative of the traffic injuries of France for year 2011. The injuries in this database were weighted [13]. The weight depends on accident and injury severity, the type of police force reporting the accident, the type of road, and the type of road users implicated in the accident.

Sample Selection and Weighting

Relevant car-to-PTW accidents in VOIESUR were selected according to the pictograms illustrated in Figure 1. These pictograms represent the accident scenarios that are likely to be tested in Euro NCAP in the upcoming years [15]. All accidents where the PTW user falls before hitting the car were left out of the sample. VOIESUR pictograms 104 and 105 represent rear-end accidents with the head vehicle respectively maintaining its speed or decelerating. In this study, the head vehicle was the PTW and the follower vehicle was the car. Pictogram 302 represents crossing accidents at intersections with vehicles coming from perpendicular directions. In this pictogram, the PTW could be coming from the left or from the right with regards to the direction of the car. Pictogram 306 represents accidents with a left turning vehicle at intersection with another vehicle oncoming from opposite direction. In our study, the turning vehicle was the car and the oncoming vehicle was the PTW.

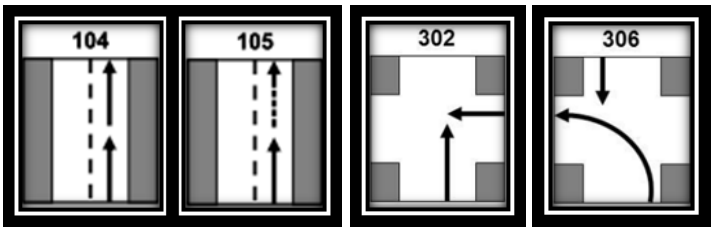


Fig. 1. VOIESUR pictograms used in this study

VOIESUR contains a certain number of accidents that cannot be re-simulated, due to lack of information about precise trajectories and speeds of the vehicles. With regards to the relevant accidents for this study, only 29% were complete with the necessary information. These accidents represent the remaining VOIESUR sample. Because of the low proportion of the remaining sample, accidents with the same selection criteria used in VOIESUR, were added from the French accident sample of the in-depth accident studies used in SaferWheels project [16]. The final sample of accidents to be re-simulated is then composed of accidents from VOIESUR and SaferWheels. However, in order to stay representative of the traffic injury situation in France, weights were attributed to the SaferWheels sample of injured PTW users selected for this study. When merging the VOIESUR and SaferWheels accident samples, it was assumed that the weight of a PTW user from the SaferWheels sample was equivalent to the mean weight of a PTW user with the same global injury level and the same accident severity level from the VOIESUR sample. In the end, new weights were attributed to PTW users, depending on global injury severity and accident pictogram, as shown in equation (1), in order to be representative of the relevant VOIESUR sample.

$$Nrem_{Inj,Picto} * \ W_{Inj,Picto} = Nini_{Inj,Picto} \quad (1)$$

Where $Nrem_{Inj,Picto}$ is the number of PTW users with an injury severity (Inj) and belonging to a pictogram (Picto) in the accidents from the remaining VOIESUR sample and SaferWheels sample, $W_{Inj,Picto}$ is the weight assigned to these PTW users, and $Nini_{Inj,Picto}$ is the number of PTW users with same injury severity and belonging to the same pictogram in the relevant VOIESUR sample.

Injury Risk Curves

AEB-PTW effectiveness assessment involves injury mitigation as well as accident avoidance. This requires injury risk curves for fatal, severe and slight injury levels. Thus, a polytomous regression was used instead of a binary regression. Two types of regression were tested, such as logistic and complementary log-log regression (CLOGLOG), as well as several independent variables (closing speed, impact speed of the car, impact speed of the PTW). The different tested configurations are listed in Table I.

TABLE I
REGRESSIONS TESTED

Model number	Independent Variable	Type of Regression
Model 1	Closing Speed	CLOGLOG
Model 2	Closing Speed	Logistic
Model 3	Car Impact Speed	CLOGLOG
Model 4	Car Impact Speed	Logistic
Model 5	(Car impact Speed) ^{2}	CLOGLOG
Model 6	(Car Impact Speed) ^{2}	Logistic
Model 7	(Closing Speed) ^{2}	CLOGLOG
Model 8	(Closing Speed) ^{2}	Logistic
Model 9	Car Impact Speed and PTW Impact Speed	CLOGLOG

As injury severity is an ordered variable, the proportional odds model was used [16]. The assumption for this type of model is that the slope would be equivalent for all levels of the response variable (probability of fatal injury and probability of fatal or severe injury). This assumption was tested for each model and when the assumption was rejected, the same model with unequal slope was built.
The nine models were compared according to two criteria:

- the Akaike information criteria (AIC)
- the calculation of expected numbers of fatally, severely, and slightly injured PTW users according to the risk curves. These numbers should be as close as possible to the real numbers in our sample: 77 fatally injured, 1,301 severely injured and 1,671 slightly injured PTW users.

Accident Reconstruction and Functional Simulation of AEB System

The last few metres of pre-crash vehicle trajectories were modelled, going as far back in time as the available data would allow, and trajectory types were restricted to portions of circles or straight lines, or combinations thereof, with constant acceleration or deceleration. For vehicle turning left across paths configurations, mostly straight-line travels prior to left turn were reconstructed, to be as consistent as possible with the accident location and known car directions prior to crash.

Eventually, impact speeds and angles, cruising speeds and possible accelerations/decelerations prior to collision, trajectory radiuses of curvature, and whether car was turning right, left, or going straight, were reconstructed for all relevant accidents. Visibility masks (fixed and mobile) were also coded.

With the purpose of simulating the response of AEB-equipped vehicles in real-life accidental situations and comparing simulated and actual outcomes, a simulation tool was developed in Matlab (*Mathworks*; Natick, Mass., USA). The inputs to this tool are accident scenarios described by car and PTW pre-crash trajectories. Obstacles are either mobile - described by their trajectories - or fixed 2D shapes, described by their relative position to the vehicle. Tool parameters include AEB sensor (number, range, vision angle, tilt angle relative to vehicle's direction of travel, longitudinal and lateral position on the vehicle, detection delay, detection type (*full* or *partial*)) and braking characteristics (rise in brake pressure delay, maximal value (full braking) and slope (full braking delay)).

For braking to start, the chosen AEB logic requires all of the following conditions to be satisfied:

a. The PTW has entirely remained in the sensor's Field-of-View (FoV) for a user-defined detection time. If more than one sensor is present, this condition has to be fulfilled by at least one of them.

b. The PTW lateral distance, relative to the vehicle's direction of travel, has been lower than a maximal distance throughout the whole detection and tracking time.

c. The model-computed Time to Collision (TTC) becomes lower than a user-defined maximal value.

Once the decision to brake is made, braking does not start immediately, but after a (user-defined) rise in brake pressure delay. And when this is passed, the user-defined maximal braking value (maximal deceleration in m/s2) is not reached immediately but after a linear increase over a (user-defined) full braking delay. The braking timeline is similar to what was used in [8].

The logic for AEB-PTW in Left-Turn-Across-Path configurations is slightly different: braking by AEB will only occur once the vehicle's left turn has started. This strategy is meant to avoid vehicle braking upon detection of any PTW travelling in the opposite direction, in the opposite lane.

The outputs of this tool are car and PTW trajectories (these are determined using a rigid body vehicle model that computes the kinematic response to the AEB-controller input, which in turn depends on the braking profile) TTC at PTW detection by the AEB system and distribution of accident outcomes

In terms of limitations / additional features, the authors would like to mention that in its present state, the tool doesn't include any complex model of the driver nor of the driver's reaction to FCW/AEB warning signals (these are not part of the model either). The virtual driver here is a simple trajectory follower. This might result in over-optimistic assessments of AEB effectiveness. Original drivers' pre-crash braking manoeuvres (if any) are taken into account if and only if they occur prior to AEB's start-of-braking moment (they are not taken into account if they occurred afterwards). Simulations from this paper used an *AEB supplements driver braking* hypothesis.

Vulnerable road users that become hidden, e.g., by an obstacle, during detection are taken into account. Options include detection time resets to zero (*Forget* option) or detection resumes (*Remember* option) when the vulnerable road user becomes visible again. The *Remember* option was used for all simulations in this paper.

The tool accommodates road conditions, e.g., ice, rain, from the original accident by reducing the possible maximal braking values. It also accommodates light conditions (blinding sun, night with or without public lighting) from the original accident by reducing the extent of the sensors' fields of view to half-range, half-angle. Each sensor is associated with a *sensitivity to light* attribute, which allows night conditions, for instance, to have an influence on parts of the sensor setup and not on its entirety. Detection or identification errors are not taken into account, neither are visibility hampering meteorological conditions. The tool accommodates limits to the vehicle speed reduction caused by AEB, for more realism, making speed reduction capped to e.g., 50 kph.

Assessed AEB Settings

Three system setups were assessed in this study, differing by the number, angle, range, and light sensitivity of their sensors. They are referred to as single, bi and triple sensor systems with settings given by Table II, Table III and Table IV respectively.

TABLE II
Single-Sensor Setting

Sensor number	Vision Angle	Range	Night Sensitive	Position & tilt
1	60°	80 m	Yes	Mid-windshield, 0°

TABLE III
Bi-Sensor Setting

Sensor number	Vision Angle	Range	Night Sensitive	Position & tilt
1	60°	80 m	Yes	Mid-windshield, 0°
2	120°	60 m	No	Mid-car front, 0°

TABLE IV
Triple-Sensor Setting

Sensor number	Vision Angle	Range	Night Sensitive	Position & tilt
1	150°	120 m	No	Car left corner front, 45°
2	150°	120 m	No	Car right corner front, -45°
3	100°	150 m	Yes	Mid-windshield, 0°

For all systems, detection delay was set to 0.2 s, maximal TTC to 1 s and maximal lateral distance to 2 m. Maximum deceleration was set to 0.9 g, to be reached linearly over a full braking delay of 0.3 s, after a rise in pressure delay of 0.05 s.

III. RESULTS

Sample Selection and Weighting

VOIESUR represents 13,285 accidents (weighted) between cars and PTW including 383 fatally, 5,239 severely, and 9,731 slightly injured PTW users. The VOIESUR relevant sample represents 2,650 accidents (weighted) including 77 fatally, 1,301 severely, and 1,671 slightly injured PTW users. Figure 2 illustrates the distribution of the PTW users of the relevant VOIESUR sample over the various pictograms and injury severity levels. Pictogram 306 represents the highest number of injuries with regards to all injury severities, followed by pictogram 302. The accidents of pictograms 104 and 105 were added together, because of the small number of accidents and injuries attributed to these pictograms.

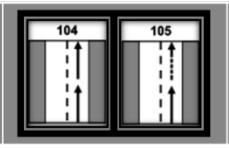
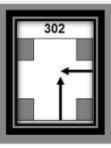
Number of injured PTW users (weighted)			
Fatal	2	32	43
Severe	127	391	783
Slight	141	730	800

Fig. 2. Number of injured PTW users (weighted) in the relevant VOIESUR accident sample, distributed over pictograms and maximum global injury in the accident.

As explained in the methods section, a significant number of accidents in the VOIESUR relevant sample were not suited for accident simulation. Thus, car-to-PTW accidents satisfying the same criteria as VOIESUR relevant sample were selected from the SaferWheels study and added to the VOIESUR remaining sample. Fig. 3 illustrates the sample selection process and the accident sample size which is finally constituted of 72 raw accidents (56 from VOIESUR and 16 from SaferWheels) weighted to be representative of the relevant accident sample. These raw accidents are distributed over pictograms and injury severities, showing also if they are from VOIESUR or from SaferWheels. It is noteworthy to mention that information available from VOIESUR did not allow the simulation of any slight injury accidents. All the latter accidents were available only from the SaferWheels sample.

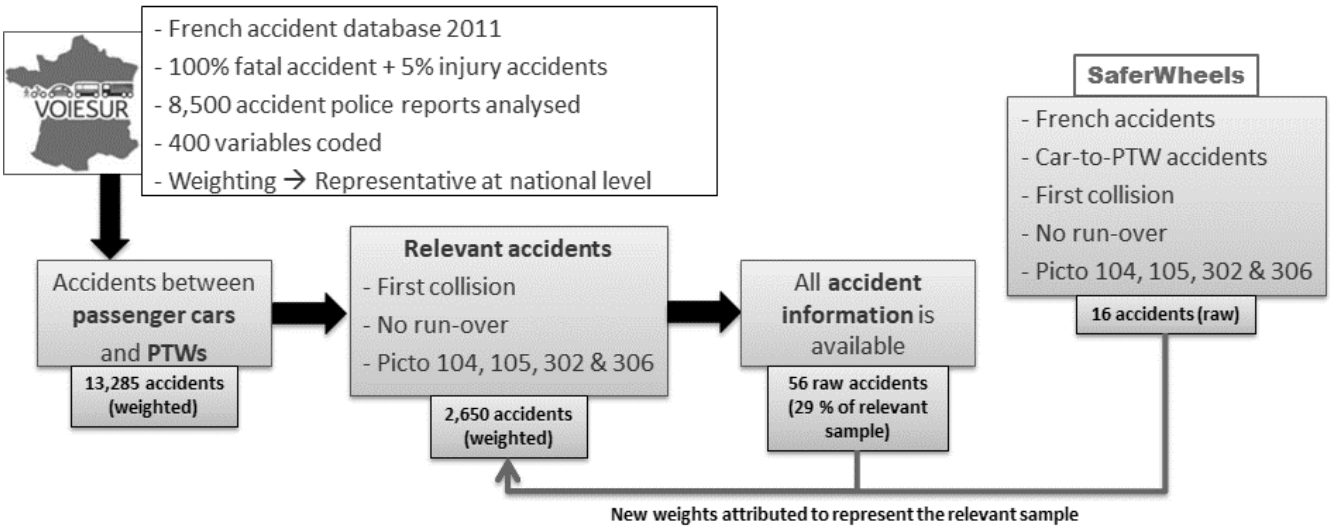


Fig. 3. Accident selection process from VOIESUR and SaferWheels databases.

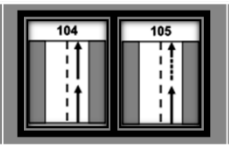
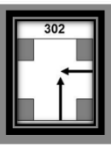
Number of Accidents (pictogram vs severity)			
Fatal	2 + 0 = 2	13 + 1 = 14	28 + 2 = 30
Severe	2 + 0 = 2	3 + 3 = 6	8 + 0 = 8
Slight	0 + 4 = 4	0 + 1 = 1	0 + 5 = 5

Fig. 4. Number of accidents that were re-simulated, originating from the remaining VOIESUR sample (in black) added to accidents from SaferWheels sample (in grey), distributed over pictograms and maximum global injury of PTW users in the accident (not weighted)

Injury Risk Curves

Table V provides the AIC values for each model. When the assumption of equal slope was rejected, the model was tested with the unequal slope specifications.

TABLE V
RESULTS

Model number	Independent Variable	Link function	Slope	AIC	Calculated – expected number		
					Fatally Injured	Severely Injured	Slightly Injured
Model 1	Closing Speed	CLOGLOG	Equal	4043.007	-2.57	-7.78	10.35
			Unequal	3994.971	-0.82	-7.04	7.86
Model 2	Closing Speed	Logistic	Equal	4074.174	1.32	-6.26	4.94
			Unequal	4049.212	4.37	-2.41	-1.96
Model 3	Car Impact Speed	CLOGLOG	Equal	4647.003	-0.36	-2.66	3.02
			Unequal	4648.890	-0.29	-2.65	2.94
Model 4	Car Impact Speed	Logistic	Equal	4667.002	1.04	0.28	-1.32
Model 5	(Car impact Speed) ²	CLOGLOG	Equal	4627.055	5.22	-11.86	6.64
			Unequal	4602.291	0.67	-5.47	4.79
Model 6	(Car Impact Speed) ²	Logistic	Equal	4645.037	1.63	1.84	-3.47
			Unequal	4626.943	0.55	-0.80	0.25
Model 7	(Closing Speed) ²	CLOGLOG	Equal	3904.527	-2.81	0.95	1.84
			Unequal	3898.186	0.12	-3.73	3.61
Model 8	(Closing Speed) ²	Logistic	Equal	3938.688	1.4	-0.64	-0.76
Model 9	Car Impact Speed and PTW Impact Speed	CLOGLOG	Equal	3533.046	1.48	-2.67	4.15

Considering both the AIC and calculated numbers, Model 8 was chosen as the model that best fits our data. The equations giving the probabilities for the PTW users to be fatally, severely, and slightly injured, are then as follows (CS=Closing Speed, in m/s):

$$P(Fatal) = 1/(1 + exp\big(-(-6.1908 + 0.00696 * CS^2)\big)) \quad (2)$$

$$P(Severe) = 1/(1 + exp(-(-1.847 + 0.00696 * CS^2))) - P(Fatal) \quad (3)$$

$$P(Slight) = 1 - P(Fatal) - P(Severe) \quad (4)$$

The injury risk curves are plotted with the above equations while representing the speed axis in kph (Fig. 5).

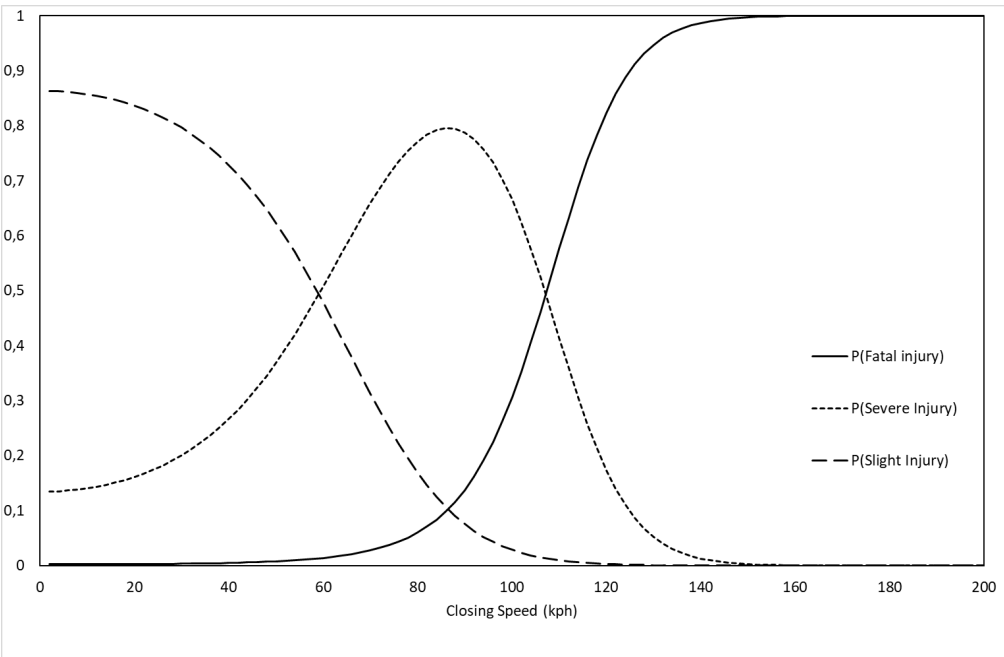


Fig. 5: Injury risk curves for PTW riders.

Effectiveness Results

Assessing AEB effectiveness consists of comparing outcomes from the original population of accidents to the outcomes of their simulation with AEB in operation. Amongst all possible metrics for this assessment, we chose to estimate the effectiveness based on equation (5).

$$E_{inj} = 100 * \frac{N_{injini} - N_{injAEB}}{N_{injini}} \quad (5)$$

with E_{inj} the effectiveness for a given injury severity level, N_{injini} the original number of PTW users at that injury severity level, and N_{injAEB} the number of PTW users remaining at that injury severity level after AEB simulation.

Evaluating the expected number of casualties is based on combining injury risk curves with accident outcome (closing speed in the present study) distributions, for both the original and the simulated accident population. This enables the computation of new probabilities for the PTW users getting injured. The probability is then multiplied by the PTW user's statistical weight and the sum of these products for all the sample gives the number of killed or injured. Only in the simulated accident population might avoided accidents (resulting in a *0 km/h* closing speed) occur. Avoided accidents have injury probability zero, regardless of injury level.

Effectiveness results for the three assessed sensor settings, in the three levels of injury severity, are given by Table VI. For the same settings, results are also given as the number of expected casualties (Fig. 6)

TABLE VI
EFFECTIVENESS RESULTS FOR VARIOUS SENSOR SETTINGS.

Setting / Injury	Fatal	Severe	Slight
Single-Sensor	48%	30%	10%
Bi-Sensor	64%	43%	21%
Triple-Sensor	75%	54%	20%

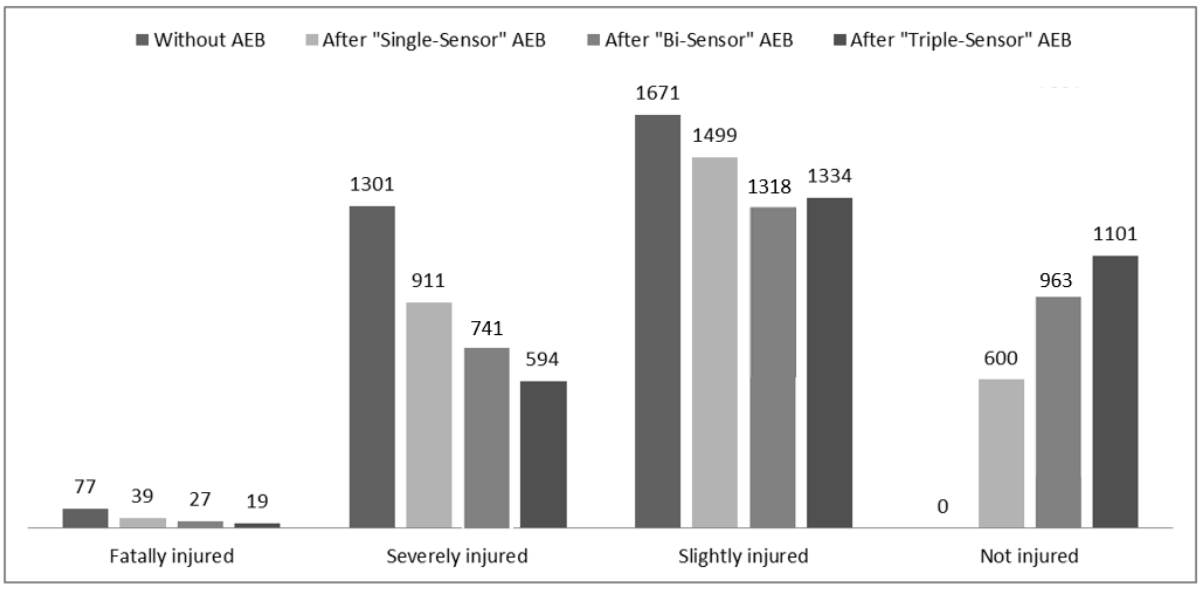


Fig. 6. Weighted distributions of injured PTW users before AEB simulation and after application of the three assessed systems

In order to reach a relatively good level of effectiveness for the three accident configurations considered for PTW, one has to select the *triple-sensor* setting. This is especially true for the most severe injuries (fatal and severe). This is even more obvious when considering the number of powered-two-wheelers accidents avoided (characterised by closing speed zero by the tool): whereas the *single-sensor* setting avoids one injury accident out of three (Fig. 7-b) in our original sample, the *triple-sensor* setting avoids approximately two such accidents out of three (Fig. 7-d).

The *triple-sensor* setting is shown to have different effectiveness values in different accident configurations (Table VII). It is especially effective in accidents where PTW are rear-ended by passenger cars, less so in straight crossing path configurations, which are often made more complex by obstacles or visibility masks – even for sensors. As to the left turn across path with oncoming PTW configuration, while the effectiveness is good for fatal injuries (70%), it is less so for severe injuries.

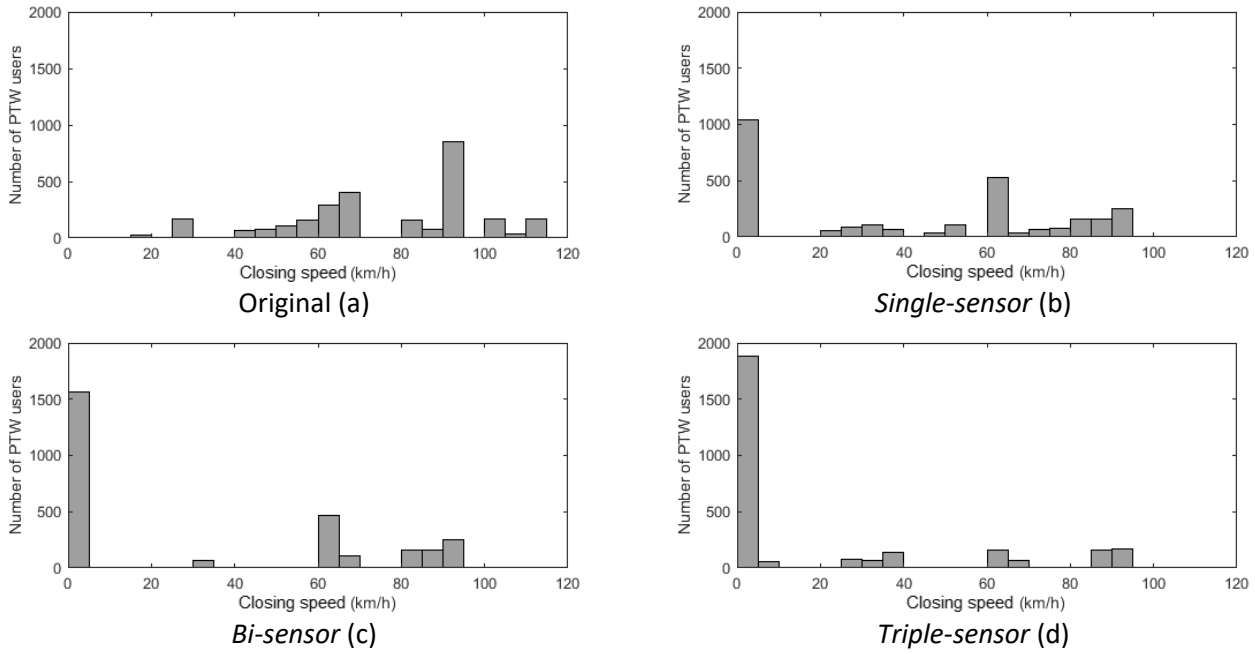


Fig. 7. Weighted original (a) and simulated closing speed distributions (b), (c) and (d) for the assessed systems.

TABLE VII
EFFECTIVENESS RESULTS FOR ACCIDENT CONFIGURATIONS USED IN THIS STUDY

Accident Configuration / Injury	Fatal	Severe
Straight Crossing Paths	84%	64%
Left Turn Across Path	70%	49%
Rear-End	100%	71%

IV. DISCUSSION

The computation of AEB-PTW effectiveness in this study is based on injury risk curves that were developed using data from real car-to-PTW accidents. These curves represent the risk of being slightly, severely, and fatally injured, for a motorcyclist colliding with a passenger car in accident configurations where AEB could be beneficial. The only study found in the literature [12] predicted a 70% risk of MAIS3+ or fatal injuries at a closing speed of 140 km/h, while in our study, such closing speed means a 99% risk for the PTW user of becoming fatally injured. One explanation could be that the sample selection and data filtering in the mentioned study excluded the cases where the most severe injury was due to the impact with the ground and not with the car. This distinction is not available in the VOIESUR database but could explain that the predictions in our study are more pessimistic.

Injury risk have been modelled with car or PTW impact speed and closing speed as independent variables. Other crash-related variables could have an influence on the injury outcome of the PTW user, such as the angle and the point of impact on the passenger car. The angle between the car and the PTW just before collision is partly taken into account as it participates in the closing speed calculation. Location of the impact point of the PTW on the passenger car, such as front left, front centre, front right, is described in the VOIESUR database. However, because of the small sample size, the focus was made on the most influential independent variables, which are mainly speed variables. This makes the injury probability dependent on speed calculation errors due to possible unprecise input parameters. Speed error range was estimated neither in VOIESUR nor in SaferWheels. Lower and higher speed estimation could have respectively shifted the injury risk curves to the left and to the

right. A simple shift to the left or to the right of the injury risk curves would not have high influence on injury probability, supposing that speed reduction due to AEB is unchanged. AEB systems using single-sensor and bi-sensor settings, even with smaller detection angle and range than what was used in the present study, were shown to be very effective in reducing pedestrian and cyclist injuries after a frontal collision with a passenger car [6][9]. This study shows that only the triple sensor based AEB system allows to keep the same level of effectiveness in reducing PTW users' injuries. This setting is a steep upgrade from AEB-Pedestrian or AEB-Cyclist settings: sensor numbers (three instead of one or two), ranges (reaching up to 150 m) or angles (a global angle of 240°). This is also a hint that addressing the issue of car-PTW accidents may require the development of rider assistance systems for PTW, as driving assistance systems for cars might not be up to the task when used alone.

The results of this study are consistent with studies using wide sensor angle and range showing high effectiveness of autonomous braking systems in reducing accidents and injuries [18]. However, no study was found dealing with AEB effectiveness in car-to-PTW accidents. The only study [11] that estimated potential effectiveness of AEB-PTW systems has focused on market penetration rates and used effectiveness values from studies of AEB effectiveness in car-to-car accidents.

One important aspect of the results is the fact that the various systems show less effectiveness for less severe injuries. For less sophisticated sensor systems, this could be due to the motorcycle staying out of sensor field of view, especially when the car speed is lower than motorcycle speed in the SCP and LTAP/OD accident configurations. The same tendency, but with lower effect, was also noticed when dealing with AEB-cyclist effectiveness [9], but not with AEB-pedestrian effectiveness [6], as pedestrian speeds would always be very low, when compared with car speeds before impact. Another explanation for the lower effectiveness for slight injuries is the fact that many of the mitigated fatal and severe injuries would be transformed to slight injuries. This is mostly noticed in the left turn across path configuration, for which the authors noticed that almost none of the slight injury accidents were avoided. The explanation for this is as follows: in most turn across path accidents, the AEB equipped simulated vehicle still stops across the original PTW's path. If closing speeds are sufficiently high (as in accidents with severe injury outcomes), it is of no consequence, as the AEB equipped vehicle's braking allows the PTW to sweep across and avoid the collision. If closing speeds are low (as in accidents with slight injury outcomes), the collision still occurs, but at a different spot on the vehicle and almost invariably when the vehicle has already come to a halt. This is caused by the simulation retaining the original reconstructed PTW trajectory. In real-life, however, PTW travelling at low speeds may have more time or more space to swerve aside when facing the AEB equipped vehicles that are in the process of slowing down themselves, and thus avoid the collision. This would cause the results presented in this paper to be overly pessimistic for these specific accidents configurations (left turn across path, slight injury accident) and also explains why there is no obvious difference between the bi-sensor and the triple-sensor configuration for slight injuries. To be more realistic and capture this effect, a model of the PTW rider reaction would be needed: this is beyond the scope of the present study but is a very interesting way of progress for future works.

While the AEB-PTW with a triple-sensor setting showed relatively good effectiveness for all accident configurations combined, it appeared to be less efficient in the left turn across path with oncoming PTW. One explanation for this result is the fact that the closing speeds in this accident configuration would be mostly due to the PTW speed and not to that of the car that is undertaking a left turn manoeuvre. Thus, even if the AEB was able to completely stop the car, it will not enable high mitigation of PTW users' injury due to the low reduction of relative speed. One solution to mitigate more injuries in this kind of accident configuration could be the use of AEB systems for motorcycles as was investigated in a study [19].

One limitation of the present study is the low sample of slight injury accidents. The PTW users involved in these accidents were given high weight values, thus making effectiveness results very sensible to a small variation in this sample. Another limitation is that nominal system design was supposed without taking into account parameters like system failure due to lack of maintenance. The system was supposed to detect the PTW a certain time after it enters the field of view, while in real life situations false negatives can happen, meaning that the system would not identify the PTW even though it was in the sensor's field of view. Furthermore, vehicles equipped with AEB are also equipped with forward collision warning (FCW) systems. These systems are designed to warn the driver about an impending collision. When simulating the effect of AEB in this study, the authors did not take into account the effect of FCW systems combined to the effect of AEB. Modeling FCW systems' effect would require modelling of driver behaviour due to the warning.

The authors would also like to underline that the present study may not be transposable to a context where no regulations on helmets exist (injury risk curves may be very different in such a context). In the sample of

accidents used in this study, all PTW users were wearing helmets.

V. Conclusions

This is the first study that highlights the potential effectiveness of AEB systems in car-to-PTW accidents. It shows optimistic results, taking into account nominal system settings and sophisticated sensor features. This is also one of the first studies to build injury risk curves for PTW users and use them to assess AEB-PTW effectiveness in car-to-PTW crashes. In the selected array of use cases, AEB-PTW was shown to effectively reduce fatal and severe injuries in the selected use cases, at the cost of a steep upgrade of AEB sensor settings, as compared to other types of AEB.

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