Prediction of motorcyclist serious injury in powered two-wheeler to other vehicle urban crash

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Abstract The aim of this study is to estimate the risk of serious injury for a motorcyclist involved in PTW-to-OV crashes occurred on urban roads. The automotive industry has already developed automatic crash notification algorithms for car occupants and knows well the influence that many crash variables have on the risk of serious injury. A literature review on the prediction of motorcyclist injury severity did not show models based on crash variables, except for crash types and, sometimes, impact speed.

Road accidents involving seriously injured riders were selected from the in-depth study of serious road accidents in Florence (InSAFE). Logistic regression techniques were applied to the total of relevant road accidents, in order to find a risk function. The results showed that the risk of serious injury (or major trauma) increased with delta-V of the motorcycle and the other vehicle and personal characteristics, such as the body mass index (BMI). It was found that the capability to discriminate between two states of severity was significant.

Keywords Risk function, Motorcyclist injury prediction, Injury severity, Logistic regression, Major trauma.

I. INTRODUCTION

Road accidents are the primary cause of death for people aged from 15 to 24 years and are the ninth highest cause of death worldwide (approximately 1.25 million casualties per year). Road accidents also represent the primary cause of disability-adjusted life years (DALYs, years of life lost to ill-health) for young people, affecting both health and economic development [1-2].

Predicting injury severity in a traffic crash for car occupants and powered-two wheeler (PTW) riders is of paramount importance. The European Parliament has fixed 2018 as the adaptation date for the advanced automatic crash notification (AACN) technology (eCall) on all new cars. The regulation will not apply to motorcycles, however. AACN systems have been broadly studied and developed, especially in the USA and Japan. The usefulness and efficacy of AACN algorithms in selecting the most appropriate hospital (in terms of level of expertise) with reference to the trauma severity is now state-of-the art [3]. A proper choice of trauma centre means the victim receives more appropriate and faster treatment for the specific trauma suffered. In addition, early access to the emergency medical system (EMS) reduces the fatality rate, especially in extra-urban and rural roadway collisions [4].

Malliaris *et al*. [5] proposed URGENCY, the first algorithm for predicting injury risk for car occupants. They found 23 significant variables and derived several different algorithms from the combination of such predictors. They started from the simplest set of rules, with only delta-V of the vehicle, and ranged up to the most complex set, taking into account seatbelts, airbag deployment, occupant position, area of damage and several other parameters to augment the precision of the algorithm. Later, Augenstein *et al*. [6] improved and validated the algorithm.

Literature review on injury risk prediction for PTW riders and pillion passengers doesn't show models based on crash variables, except for impact speed and crash configuration (e.g. head-on, head-on side, rear-end, etc.). The papers sourced focused mainly on demographic and environment-related risk factors, such as type of vehicle, motorcyclist's condition (e.g. alcohol use, age, crash location and time, weather and light conditions, helmet use, roadway characteristics, etc. and not on variables directly related to the vehicle crash phase.

Trauma scores are used to classify trauma severity. A scoring system can be classified as anatomical (using scores that indicate trauma severity), physiological (measuring injury dynamic component) or combined (using

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both anatomical findings and physiological measurements) [7]. Among anatomical scoring systems we can include Injury Severity Score (ISS), while Revised Trauma Score (RTS) and Trauma and Injury Severity Score (TRISS) are, respectively, physiological and combined systems. It is not completely clear which score predicts trauma severity most accurately, due to the heterogeneity of population studies, mechanism of trauma and type of care [8-10].

The aim of this study, therefore, is to establish a first injury risk function able to predict the major trauma of a rider involved in a PTW-to-OV (other vehicle) urban crash.

II. METHODS

Predicting rider injury severity in real-world crash scenarios can lead to significant improvement of post-crash rescue procedures, enabling emergency personnel to alert and select the most appropriate rescue service and hospital. Injury severity prediction models are commonly based on variables that can assess the probability of major trauma. A statistical analysis was conducted to find those variables that could better predict the severity. The analysis was carried out on a sample of real-world urban accidents, selected according to the following criteria: (i) the motorcyclist was admitted to ICU due to a major trauma diagnosis; (ii) the OV was a car or a van; and (iii) the PTW hit the OV with its frontal part (i.e. head-on and head-on-to-side crash scenarios).

A dataset of 40 cases from the InSAFE database corresponded with the selection criteria.

Data source

The in-depth study of road accidents in Florence (InSAFE) is an in-depth crash investigation study conducted by the University of Florence jointly with the intensive care unit (ICU) of the Careggi University Hospital [11-12]. The InSAFE database has been collecting serious road accident data since 2009 in the city of Florence and its environs. The inclusion criteria were major trauma for at least one person involved in the crash, and subsequent admittance to ICU. The occurrence of a crash fulfilling the criteria was notified by the ICU within 24 hours of hospital admission. The database comprises 129 serious crashes relating both to vulnerable road users (pedestrians, cyclists, and motorcyclists) and car occupants.

Data Collection and Accident Reconstruction

Crash scene, vehicles and passive safety systems like airbags and seatbelts, as well as personal protective equipment (PPE – helmet, jacket, suit, etc.), were examined retrospectively. A crash reconstruction was carried out to assess the crash conditions (e.g. crash angle, impact speed and delta-V), and to correlate injuries to crash dynamics and causes. Empirical equations were used to estimate the energy absorption by the PTW when it was subjected to a wheelbase shortening (Equations (1) and (2)) [13-14] and to calculate the impact speed, delta-V and relative speed (Vr). Momentum and energy analysis were used for those cases where the PTW did not show a wheelbase reduction.

$$E_{d,PTW} = \frac{1}{2} m_{PTW} \left(b_0 b_1 + b_1 d_{PTW}\right)\left(k \cdot d_{car} + \delta\right) \qquad E_{d,car} = \frac{1}{2} \cdot m_{PTW} \left(102.1 + 1451.6 \cdot d_{PTW}\right)\left(k \cdot d_{car} + \delta\right) \tag{1}$$

$$E_{d,PTW} = m_{PTW} \cdot 641.7 \cdot \left(\Delta p_{PTW} + 0.1\right)^{1.89} \qquad E_{d,car} = 65305 \cdot \left(d_{car} - 0.0576\right) \tag{2}$$

where:

$b_0 b_1$	=	Stiffness coefficients	d_{PTW}	=	PTW wheelbase shortening
k	=	Shape factor equal to 0.564	d_{car}	=	Car maximum damage
δ	=	Elastic deformation	m_{PTW}	=	PTW mass

Multibody simulations with Virtual Crash 2.0™ software [15] were used to optimise the vehicle impact conditions in terms of relative position, change in velocity (delta-V) and energy absorbed through evidences, motorcyclist injuries and analytical results and to calculate the vehicle impact speeds. The process stopped when the deformation energy, estimated with multibody simulation, was included in the range of ±20% of the analytical solution.

Total body computer tomography (CT), X-ray and magnetic resonance imaging (MRI) were used by the InSAFE team to codify injuries through the abbreviated injury scale (AIS) [16]. Anatomical and physiological scores were used to assess the motorcyclist outcome. The first scores were the maximum abbreviated injury scale (MAIS), the injury severity score (ISS) and the new injury severity score (NISS). While the physiological scores were the revised trauma score (RTS) and the trauma and injury severity score (TRISS).

Statistical methods

Crash variables like impact configuration, impact speed, delta-V, Vr and absorbed energy, and rider information like helmet type (full or open face), helmet loss, age and body mass index (BMI), were investigated by binary logistic regression analysis to predict the motorcyclist's risk of major trauma. The risk of major trauma has been defined both in terms of ISS and RTS scores.

The probability of suffering a major trauma (ISS≥15) can be defined using a logistic function (Equation (3)):

$$P_{(ISS\geq 15|X)} = \frac{1}{1+e^{-(\beta_0+\sum_{j=1}^{p}\beta_j X_j)}} \tag{3}$$

where β_i are the regression coefficients and X_i are the explanatory variables (or predictors).

By means of the inverse of the logistic function (log odds or logit), we can write a linear relationship between the logit and the predictors (Equation (4)).

$$\hat{Y} = \ln\left(\frac{P_{(ISS\geq 15|X)}}{1-P_{(ISS\geq 15|X)}}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \tag{4}$$

Backwards stepwise likelihood ratio elimination approach was used to identify the best subset of predictors. In this case, the explanatory variables were iteratively removed from the model if their significance violated a p-value cut-off point of 0.1.

The Wald Chi-Square test was used to validate whether the predictors had a statistically significant relationship with risk of major trauma in motorcyclists. The null hypothesis assumes that the predictors had no effect on the risk of major trauma. Chi-Square test and p-value were calculated. If the p-value was lower than 0.05, the predictors had a statistically significant relationship with the risk of major trauma.

A cut-off value for P(ISS≥15|X) was fixed at 0.5. This means that a probability greater than or equal to the cut-off value was judged as a serious injury (major trauma). The quality of the discriminatory capability of the model was assessed by the area under the receiver operating curve (AUC).

III. RESULTS

Crash data analysis

The sample studied consisted of 40 PTW-to-OV serious metropolitan crashes involving riders admitted to ICU for major trauma diagnosis.

The head-on-to-side collisions had a frequency of 62.5% (25/40), and the head-on collisions of 38.5% (15/40). Among the head-on collisions, in five cases the rider hit frontally into the back of an OV.

Scooters (67.5%, 27/40) were more frequently involved than motorcycles, as well as cars, among the OVs (72.5%, 29/40). Van (12.5%, 5/40) and SUV (15%, 6/40) showed a similar proportion.

In 12 cases (30%) the rider fell before impacting with the OV and none ABS system was present. The motorcycle impact speed ranged from 15 km/h to 88 km/h, with a mean value of 44.8 km/h (SD 13.02). The OV's impact speed had a mean value of 22.8 km/h (SD 14.9, range 0–58 km/h).

Motorcyclist characteristics

Forty motorcycle crash victims, all of whom were admitted to the trauma centre of Careggi Hospital and then to the ICU, were included in the study. The dataset included only one female.

The sample age ranged from 15 to 63 years, with a mean of 33.1 years (SD 14.0). Young people constituted the majority of the sample: the median was 34 years, and 82.5% were aged less than 45 years.

The BMI ranged from 17.3 to 32.1 with a mean of 24.5 (SD 2.6) and a median of 24.7.

Every motorcyclist was wearing a helmet during the crash, and in seven cases it was lost during the impact. Helmet data were available for 6.5% of the cases. Twenty percent of the motorcyclists were wearing a full-face helmet and 42.5% an open-face one.

Only 55% (22/40) of the riders were subjected to an alcohol test, and 3 out of 21 riders (14.3%) were positive.

Injury severity

Thirty-day mortality was low (5%, 2/40). The two victims who died in ICU died 2 and 7 days after the crash, respectively.

The ISS ranged from 4 to 54 (Fig. 1). Following the InSAFE inclusion criteria, the number of victims with an ISS lower than 15 was limited (7 patients). Fifty percent of the sample suffered an ISS lower than 22, and the most common score was 29 (15%) (Fig.1).

The Glasgow Coma Scale (GCS) evaluated on the scene of the accident was known in 92.5% of the cases. The median value was 10.9. Twenty victims were in the range 13–15 (mild or no traumatic brain injury (TBI)); four victims were in the range 9–12 (moderate injury) and 13 victims were in the range 3–8 (severe injury).

RTS and TRISS could be estimated in 30 patients. The RTS ranged from 2 to 7.8, with a mean of 6.6 and a median of 7.2 (12 is labelled delayed, 11 is urgent, 3–10 is immediate).

The survival probability (TRISS) ranged from 0.14 to 0.99, with a mean of 0.87. Both median (0.95) and mode (0.98) were high according to the survival rate (95%) (Table I).

TABLE I

DISTRIBUTION OF THE SEVERITY SCORES PER CRASH CONFIGURATION

Crash Configuration	AIS		ISS		NISS		RTS		TRISS		GCS	
	2-	3+	15-	15+	15-	15+	7-	7+	<0,5	>0,5	12-	12+
Head-on (15)	1	14	2	13	1	14	8	4	2	10	7	7
Head-on-Side (25)	2	23	5	30	2	23	6	12	1	17	10	13

Sustained injuries

A total of 365 injuries were identified in 40 victims (mean of 9.8 injuries per person). Head-Face and Upper-Trunk (thorax & thoracic-spine) were the body sections most subject to injury (33.2% and 34.5% of the total), and also the most frequently seriously injured (AIS3+). Upper and lower limbs, and lower trunk (abdomen & lumbar spine) showed a similar proportion of injuries (8.8%, 9.9% and 11.2%, respectively), but the most severe injuries occurred at lower trunk and limbs (Figs 2 and 3).

The highest number of head injuries were to the brain (45 lesions). Contusion was the most frequent injury (26.6%, AIS1-3), followed by intraventricular (15.5%, AIS2) and subarachnoid haemorrhage (11.1%, AIS2-3). Among Head-Face fractures, basilar fracture was the most common occurrence (27.9%, 19/68).

Upper trunk showed a high number of lung contusions (63.6%, 35/55) and thoracic injuries (34.5%, 19/55) (pneumothorax, hemothorax, hemopneumothorax). Among thoracic fractures there was a high percentage of vertebra fractures (29.0%, 47/163), mostly to the spinous and transverse processes, and single or multiple fractures. The sample also included three cases featuring the rupture of the aorta artery.

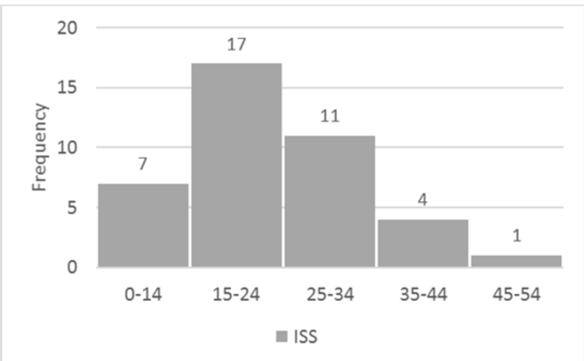

Fig. 1. Injury Severity Score (ISS) frequency.

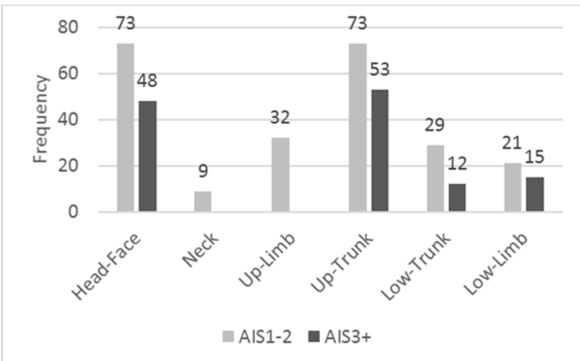

Fig. 2. Distribution of AIS1-2 and AIS3+ per anatomical region.

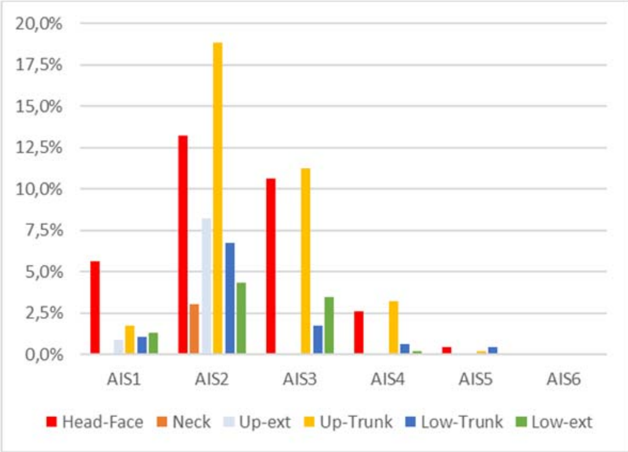

Fig. 3. Percentage of AIS per body section (461 injuries).

Injury Risk

The risk of major trauma was assessed on the following reduced subset (40 cases), according to the impact configurations: (1) head-on (HO); (2) head-on-to-side (HOS); and (3) HO plus HOS (in this case the PTW hit the OV with its frontal part). A fourth subset, based on the OV point of impact, was judged too (Fig. 4). For the latter, we recoded the HO and HOS impact configurations by the PTW point of impact on the OV based on the car shape. If the PTW hit on a back of an hatchback car (two-box), the impact was classified the same as one occurring on the lateral part of the car (part B). If the PTW hit on a back of a sedan car (three-box), the impact was classified the same as one occurring on the frontal part (A). Following this scheme, 21 impacts occurred on the part B, and 19 on the part A.

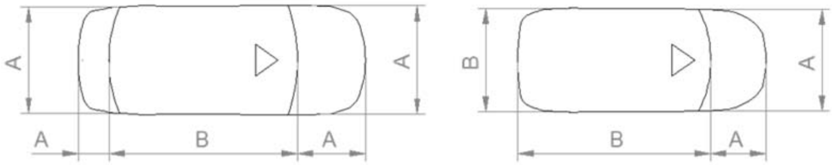

Fig. 4. Partition of crash configuration based on the car point of impact (Sedan at left and Hatchback at right).

Table III shows different injury risk models for the prediction of major trauma in terms of ISS according to the impact configurations previously defined. From the crash viewpoint, the main vehicle parameters considered for the regression analysis were the impact speed, delta-V and the relative speed (Vr), while for the rider they were age, gender, BMI and helmet type. Two-way interaction effects were also tested.

The number of predictors was chosen in a ratio of 1:10 with the sample size [17]. In the results, predictors with a significance level up to 0.2 were included.

Table IV summarises the estimates of the AUC and the adjusted R-square (Nagelkerke's R square) for logistic regression of each model. Taking as a reference an AUC statistic higher than 0.8 [18], the capability to discriminate between the two states of the binary dependent variable (ISS15+) seems to be reasonable for all the models.

TABLE III

MODEL FOR PREDICTION OF ISS≥15

Model	Impact Config.	Predictors	B	S.E.	Wald	df	Sig.	Exp(B)	C.I. Lower	C.I. Upper
1	HO	δVptw	1.285	0.941	1.865	1	0.17	3.614	0.572	22.854
		δVptw*δVcar	-0.787	0.587	1.796	1	0.18	0.455	0.144	1.439
		Constant	-6.666	4.876	1.869	1	0.17	785.18		
2	HOS	δVcar	2.035	1.186	2.942	1	0.09	7.649	0.748	78.221
		Constant	-0.884	1.244	0.505	1	0.48	0.413		
3	HO+HOS	δVptw	0.517	0.276	3.525	1	0.06	1.677	0.978	2.878
		δVptw*δVcar	-0.362	0.176	4.204	1	0.04	0.697	0.493	0.984
		Constant	-2.460	1.325	3.447	1	0.06	0.085		
4	HO+HOS	δVptw*δVcar	-0.530	0.242	4.812	1	0.03	0.588	0.366	0.945
		δVptw*BMI	0.033	0.016	4.208	1	0.04	1.034	1.001	1.067

		Constant	-3.409	1.682	4.109	1	0.04	0.033		
5	B	δVptw	-0.162	0.094	2.967	1	0.08	0.850	0.707	1.023
		δVptw*δVcar	0.024	0.015	2.633	1	0.105	1.024	0.994	1.054
		Constant	3.377	1.89	3.194	1	0.074	29.297		

TABLE IV

AREA UNDER THE CURVE FOR ISS≥15

Model	Impact Config.	AUC (S.E.)	Nagelkerke R Square
1	HO	0.96 (0.05)	0.70
2	HOS	0.81 (0.09)	0.25
3	HO+HOS	0.83 (0.07)	0.35
4	HO+HOS	0.87 (0.06)	0.43
5	B	0.82 (0.110)	0.02

Null hypothesis: true area = 0.5

Table V shows the models for the prediction of major trauma in terms of RTS and impact configurations, and Table VI summarises their goodness of fit. PTW and OV delta-V were the most significant predictors in all the models, and no two-way interaction effects were significantly related to the RTS score. Except for model 3, all the others showed a sensible capability of discriminating between the two states RTS7- and RTS7+ (AUC > 0.8).

TABLE V

MODEL FOR PREDICTION OF RTS<7

Model	Impact Config.	Predictors	B	S.E.	Wald	df	Sig.	Exp(B)	C.I. Lower	C.I. Upper
1	HO	δVptw	0.492	0.325	2.288	1	0.130	1.636	0.865	3.096
		Constant	-3.649	2.471	2.181	1	0.140	0.026		
2	HOS	δVcar	-3.423	1.683	4.135	1	0.042	0.033	0.001	0.883
		Constant	3.256	1.813	3.223	1	0.073	25.94		
3	HO+HOS	δVptw	0.141	0.075	3.563	1	0.059	1.151	0.995	1.333
		Constant	-1.816	0.957	3.598	1	0.058	0.163		
4	HO+HOS	δVptw	0.463	0.215	4.619	1	0.032	1.589	1.042	2.423
		δVcar	-2.254	1.293	3.040	1	0.081	0.105	0.08	1.323
		Constant	-2.162	1.024	4.453	1	0.035	0.115		

TABLE VI

AREA UNDER THE CURVE FOR RTS<7

Model	Impact Config.	AUC (S.E.)	Nagelkerke R Square
1	HO	0.97 (0.05)	0.78
2	HOS	0.85 (0.01)	0.51
3	HO+HOS	0.71 (0.10)	0.22
4	HO+HOS	0.83 (0.08)	0.40

IV. DISCUSSION

A dataset of 50 PTW-to-OV crashes was selected from the in-depth investigation database in Florence (InSAFE), which records detailed information on serious urban accidents. Impact speed was estimated using calculations based on the measure (or estimation) of the vehicle damage and skid marks, and through computer reconstructions. The injury severity was coded according to the AIS scale, and the main anatomic and physiologic or mixed outcome severity scores were evaluated.

Advanced automatic crash notification (AACN) algorithms for the prediction of the car occupants' severity of injury have been studied in-depth, especially in the USA and Japan. The state-of-art points out the beneficial use of such algorithms in the right selection of optimal treatment and trauma centre and, therefore, in the reduction of mortality and morbidity. With the upcoming (2018) introduction of the eCall technology at

European level, these algorithms could also be very beneficial for two-wheeled vehicles. In the literature, many studies investigated factors that influence motorcyclist injury severity. Among the crash risk factors, the predictors that play an important role in determining accident severity seem to be the impact configuration and the speed limits [20-22]. Nevertheless, the impact speed was seldom used, and crash variables like ΔV were never considered.

According to national accident data, the number of seriously injured riders increased in 2015 by 6.4%, and the number of fatalities on urban roads was very similar to same for rural roads (44% vs. 47%) [23]. Urban roads are, therefore, as unsafe as extra-urban roads [24]. A detailed description of the injuries and trauma severity for those suffering a major trauma in the selection sample of this study can be found in Piantini *et al*. [25]. For that reason, a dataset of PTW-to-OV crashes was selected from the InSAFE in-depth database and then thoroughly analysed, paying specific attention to easy-to-measure, on-board crash data at the time of the crash.

In this analysis, the impact speed does not explain the changes in rider injury severity. Plotting the impact speed versus the injury severity score (ISS), no specific trend is evident. Except for one case where the impact speed was very high (88 km/h) for a urban road, the sample shows that the majority of the serious accidents occurred in the range of 40 to 60 km/h. Generally speaking the PTW impact speed is upper the urban speed limits, but this is also supported by an high number of speed violations certified by the police.

The majority of the sample have an ISS in the range of 15–45, with an impact speed in the range of 30–60 km/h. Regarding the ISS scores lower than 15, the number of accidents were limited and were located in the same velocity range (Fig. 4).

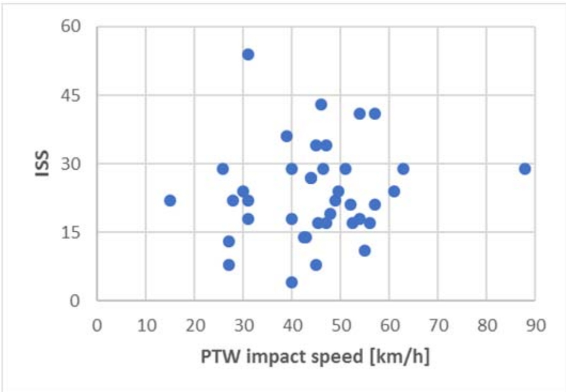

Fig. 4. PTW impact speed versus Injury Severity Score for HO and HOS impact configurations.

The small size of the sample makes it difficult to achieve a high significance level for the predictors. For this reason we have included predictors with a significance level up to 0.2.

PTW and the OV delta-V were found to be the main significant predictor of the probability of suffering a major trauma (ISS15+). Considering the overall sample (HO+HOS), the delta-V was significantly correlated to ISS at $p<0.05$ level. In the first model an increment of delta-V related to the PTW (ΔVptw) and the interaction between the delta-V of both PTW and OV (ΔVptw*ΔVov) showed an increase by 62% and 41%, respectively, in the probability of suffering a major trauma (ISS15+) in comparison to the null model (model that includes only the intercept). In the second model, which includes only the interactions ΔVptw*ΔVov and ΔVptw*BMI, the probability showed an increase of 37% and 51%, respectively. Both HO and HOS subsamples did not appear to have a sufficient statistical correlation with ISS15+, and this is most likely due to an excessive heterogeneity of each subsample in term of specific crash conditions. Nonetheless, when the cases where the PTW impacts, with its frontal part, the rear-end of the OV and the side impacts (B) were added, the significance improved somewhat.

Regarding the goodness of fit, the AUC curve showed that the logistic models have a reasonable capability of discriminating between two states of severity.

Limitations

The high severity of the patient included in our study is atypical in comparison to traditional ones conducted on people severely injured (AIS3+). InSAFE patients are all trauma patient admitted to an intensive care unit caused by a systemic failure due to, for example, the involvement of body parts as thorax (respiratory failure), head (neurologic failure) or abdomen. Patients seriously injured but without a systemic failure could not be included in our database or present but with low frequency. And this can explain the relatively high percentage of head and upper trunk lesions and the relative low incidence of limb injuries compared to international literature.

For that reason, the sampling criterion for InSAFE participants leads to a bias towards an over-representation of severe accidents. Therefore, due to the high proportion of ISS15+ (80%), the proposed models will overestimate the major trauma prediction. Therefore, the limited number of cases and the high number of seriously injured means that extra crash and injury information were not available that would have proved useful in improving the risk prediction.

V. CONCLUSIONS

In this study a dataset of 40 PTW-to-OV urban crashes were closely studied from the injury severity viewpoint, and also in terms of which measurable-on-board PTW crash data can best predict the rider trauma severity.

The area under the curve (AUC) shows a significant capability of discriminating between two states of severity, both in terms of ISS and RTS scores, even if the prevalence of ISS15+ increases the model's sensitivity and reduces its specificity.

The more significant crash predictors for injury severity prediction were found to be the impact configuration (e.g. head-on, head-on-to-side collisions, etc.) and the delta-V of both PTW and the OV.

VI. REFERENCES

[1] Mokdad, A. H., *et al*. (2016) Global Burden of diseases, injury and risk factors for young people's health during 1990–2013: a systematic analysis for the Global Burden of Disease Study 2013. 387, *The Lancet*, 387: pp.2383–401.

[2] World Health Organization (WHO). (2015) *Global Status Report on Road Safety*.

[3] Candefjord, S., *et al*. (2015) On-Scene Injury Severity Prediction (OSISP) Algorithm for Truck Occupants. *Traffic Injury Prevention*, 16 (sup2): pp.S190–S196.

[4] Evanco, W. (1999) The potential impact of rural mayday systems on vehicular crash fatalities. *Accident Analysis & Prevention*, 31 (5): pp.455–62.

[5] Malliaris, A. C., *et al*. (1997) Relationships Between Crash Casualties and Crash Attributes. *Society of Automotive Engineers, SAE* 970393.

[6] Augenstein, J. S., *et al*. (2001) Development and Validation of the Urgency Algorithm to Predict Compelling Injuries. *Proceedings of the 17th International Technical Conference on the Enhanced Safety of Vehicles (ESV)*, 2001, Amsterdam.

[7] Rapsang, A. G., Shyam, D. C. (2015) Scoring System of Severity in Patients with Multiple Trauma. *Cirugía Española (English Edition)*, 93 (4): pp.213–21.

[8] Yousefzadeh-Chabok, S., Hosseinpour, M. (2016) Comparison of Revised Trauma Score, Injury Severity Score and Trauma and Injury Severity Score for Mortality prediction in elderly trauma patients. *Ulus Travma Acil Cerrahi Derg*, 22 (6): pp.536– 40.

[9] Alghnam, S., *et al*. (2014) Predicting in-hospital death among patients injured in traffic crashes in Saudi Arabia. *Injury*, 45 (11): pp.1693–9.

[10] Ahun, E., *et al*. (2014) Value of Glasgow Coma Scale, age, and arterial blood pressure score for predicting the mortality of major trauma patients presenting to the emergency department. *Ulus Travma Acil Cerrahi Derg*, 20 (4): pp.241–7.

[11] Piantini, S., *et al*. (2012) A Pilot Study of an Integrated Accident Research System Based on a Medical and Engineering Data in the Metropolitan Area of Florence. *Proceedings of IRCOBI Conference*, 2012, Dublin.

[12] Piantini, S., *et al*. (2013) Advanced accident research system based on a medical and engineering data in the metropolitan area of Florence. *BMC Emergency Medicine*, 13: pp.3.

[13] Wood, D. P., *et al*. (2014) Estimation of the collision speed in a collision of a motorcycle or scooter with a car from individual vehicle deformation. *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, 228 (3): pp.295–309.

[14] Vangi, D., Cialdai, C. (2014) Evaluation of energy loss in motorcycle-to-car collisions. *International Journal of Crashworthiness*, 19 (4): pp.361–70.

[15] Belobrad, M., Sucha, V. Virtual Crash Technical Manual, 2012.

[16] Association for the Advancement of Automotive Medicine [AAAM]. (2005)

[17] Sperandrei, S. (2014) Understanding logistic regression analysis. *Biochemia medica*, 24 (1): pp.12–18.

[18] Harrell, F. E. (2001) Regression modelling strategies: with applications to linear models, logistic regression, and survival analysis. *Springer science and business media*, Inc.: New York, NY.

[19] Cudnik, M. T., *et al*. (2009) Level I versus Level II trauma centre: an outcomes-based assessment. *Journal of Trauma*, 66 (5): pp.1321–6. DOI: 10.1097/TA.0b013e3181929e2b.

[20] Mazharul, H., *et al*. (2012) An investigation on multi-vehicle motorcycle crashes using log-linear models. *Journal of Safety Science*, 50 (2): pp.352–62.

[21] Blackman, R., Haworth, N. (2013) Comparison of moped, scooter and motorcycle crash risk and crash severity. *Accident Analysis & Prevention*, 57: pp.1–9.

[22] De Lapparent, M. (2006) Empirical Bayesian analysis of accident severity for motorcyclists in large French urban areas. *Accident Analysis & Prevention*, 38 (2): pp.260–68.

[23] Bruzzone, S. (2016) Road accidents in Italy. Internet: [https://www.istat.it/en/archive/192246]. [Accessed 30 March 2017].

[24] Albalate, D., Fernández-Villadangos, L. (2009) Exploring Determinants of Urban Motorcycle Accident Severity: The Case of Barcelona. XREAP 2009-02.

[25] Piantini, S., *et al*. (2016) Injury Analysis of Powered Two-Wheeler versus Other-Vehicle Urban Accidents. *Proceedings of IRCOBI Conference*, 2016, Malaga.