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A logistic model for Powered Two-Wheelers crash in Italy

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Abstract

Italy shows the European primacy in number of powered two-wheelers fatalities (PTW), which accounts for 30% of the total, compared to the 17% of the EU average. PTWs are the most vulnerable of powered transport modes because of their lack of safety devices and the absence of a protecting chassis for drivers and passengers. Drawing on ISTAT database, a logistic regression was carried out, in order to identify factors affecting crash severity. The analysis of the results partially confirmed previous international studies and added new knowledge about the causes of injury severity in PTW crashes in Italy.

Keyword: road safety, motorcycle, moped, crash severity, logistic regression.

1. Introduction

In 2009 there are currently an estimated of 35 million PTWs, from small 50cc mopeds to powerful motorcycles, circulating in the EU 27 countries, 28.7% of which are located in Italy. These represent about 14% of the entire European private vehicle fleet (cars and PTWs only), but they account for around 19% of the fatalities (34% in Italy) [1]. This sad primacy of Italy in the number of PTW crashes and fatalities are typical of other euro-Mediterranean countries (Spain, France, Italy, Greece, Malta) and reflect the large use of powered two - wheeled vehicles in these countries due, above all, to the good climate conditions.

Worldwide the high vulnerability of PTW users produces a disproportion between the participation to traffic and the level of fatal PTW crashes. Indeed, PTWs are the most vulnerable of powered transport mode because of their lack of safety devices and the absence of a protecting chassis for drivers and passengers, which means that PTW riders are more likely to suffer fatalities than car occupant when involved in similar accidents [2].

Many researches on motorcycle accidents are conducted using an univariate approach, and focused on some risk factors, such as helmet use or riders' age, and then tried to determine their relationship with injury severity.

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The causes leading to the injury severity levels are always complicated by presence of multiple factors, including rider's characteristics (e.g., gender, age and use of restraint systems), environmental factors (e.g., weather and light conditions, urban/rural surrounding), roadway designs (e.g., horizontal and vertical alignment, segment or intersection) and other factors (e.g., collision types, collision partner). Isolating some factors for analysis and treating others as fixed does not allow one to obtain a complete understanding of the underlying causes of injury severity in motorcycle accidents.

In literature there are several studies for motorcycle severity analysis by using multivariate approaches [3] [4] [5] [6] [7]. These studies has identified many risk factors for severe PTW crashes, and also showed multinomial logit formulation as a promising approach to evaluate the determinants of injury severity in PTW accidents.

Chang [4] analyzed 2000 single – vehicle crash data to compare fatality risk factors between non – motorcycle drivers and motorcyclists. On average, motorcyclists had approximately a three times higher fatality risk than non – motorcyclists after adjusting for the driving mileage. Two respective logistic regression models for two categories of drivers indicated that some common features, such a being male, a higher age, and crashes occurring between the hours of 22 and 06 revealed a greater likelihood of fatality.

Ucar and Tathdil [6] examined motorcycle accidents occurring in 2002 in Turkey. As a result, it was determined that drivers who prefer to travel on a two-directed road, in an urban area, during the daytime have a better chance of survival in motorcycle accidents.

The crash injury severity analysis presented in the paper of Savolainen and Mannering [8] about motorcyclists' injury severities in single- and multi-vehicle crashes revealed several problem areas leading to more severe injuries: poor visibility (horizontal curvature, vertical curvature, darkness); unsafe speed (citations for speeding); alcohol use; not wearing a helmet; right-angle and head-on collisions; and collisions with fixed objects. There were some findings that motorcyclists may be managing risks. Crashes were found to be less severe under wet pavement conditions, near intersections, and when a passenger was on the motorcycle. This may indicate that riders may be riding in a more cautious manner under such situations—resulting in less severe crashes once they occur.

By developing a probabilistic model that contains several important variable relating to environmental factors, roadway conditions, vehicle characteristics and rider attributes, Shankar and Mannering [9] provide suggestive results by use of variable such as helmet sobriety interaction and helmet – fixed object interaction. Their study suggests that helmeted – riding may be an effective means of reducing injury severity in some types of collisions, however, the benefit of helmet use may be offset in fixed – object collisions where the risk of fatality was found to increase.

The study of Indriastuti et Sulistio [7] is aimed to develop a probability model of motorcycle accident in urban area, with the case study of Malang City, using logistic regression method the influencing factors on motorcycle accident were identified. The explanatory variables that significantly influenced the probability of a motorcycle rider get in an accident are gender, number of motorcycle owned, travel purpose, distance and riding knowledge.

MAIDS (Motorcycle Accidents In Depth Study) database [10] was used to calibrate logistics models in order to identify factors that may be good predictors of the PTW rider fatality. As the result of this analysis, the following major findings were observed:

- the risk of a PTW rider fatality increases with age. PTW riders over 41 years of age appear to be at greater risk. PTW riders between 18 and 21 years appear to have lesser risk of being involved in a fatality when compared to 26 to 41 year old PTW riders;
- there is a significant increase in the risk of a PTW rider fatality when the accident takes place on a major arterial roadway;
- accidents that take place at a site other than an intersection appear to have a greater risk of PTW rider fatality;
- when other factors are taken into consideration, no vehicle factors were found to be statistically significant predictors of a PTW rider fatality;

- PTW rider speeding was not found to be a good predictor of a PTW rider fatality, but for every 10 km/h increase in crash speed, the odds of a PTW rider fatality increase by 1.31.

No similar studies, based on a rigorous methodological approach, were found in the recent literature referring to the Italian case study. This lack of information is particularly serious considering that Italy represents a "leading" country in terms of number of PTW users and consequently of PTW crashes and road fatalities.

In this study logistic regression is used to examine the influence of multiple factors related to road geometry, environmental condition, collision characteristics, driver attributes and type of PTW, on road crashes involving PTW in Italy. The variables included in the models and the detailed analysis of the results partially confirmed previous international studies and added new knowledge about the causes of injury severity in PTW crashes in Italy.

2. Data treatment

In Italy, the source of data for statistics on road crashes is provided by ISTAT (National Institute of Statistics). Any injury and/or fatal accident should be reported by the police authorities using a standardized Model (CTT.INC ISTAT) [11]. The different levels of severity are:

- Killed: any person who was killed outright or who died within 30 days as a result of the accident;
- Injured: any person, who was not killed, but sustained one or more serious or slight injures as a result of the accident.

Data used in this study were extracted from the ISTAT dataset counting 78,419 crashes occurred in 2008 in which at least a moped (power of 50 cc) and/or a motorcycle (power over 50 cc) was involved [12]. Since the goal of the study was to identify the factors that might affect the severity of a PTW crash (i.e. whether it was a fatal or non – fatal accident for the PTW driver), the dependent variable "CRASH SEVERITY" (CR) was defined and treated as a binary variable, assuming the value:

CR=1 if crash results in the PTW driver fatality;

CR=0 in any other case (i.e. PTW drive injury, PTW passenger fatality/injury, opposing vehicle driver or passenger fatality or injury).

From the dataset 8 variables were selected basing on the relevance of the parameter and on the completeness of the information (some variables are not full fillet in the data set): time of day, road type, road geometry, collision type, PTW type, partner collision, age of driver, crash circumstances.

Because some variables have several codes in the crash report (e.g. crash circumstances is coded with 107 different values, driver age is an integer value ranging from 14 to 89) a first aggregation was carried out to simplify the information. Other variables were treated to define derived information (e.g. the date and hour of the crash were used to define the light condition: daylight/night time). Each categorical variable is described by several levels describing a sub-set of design variables. A model reporting many design variables can give a more detailed analysis of the phenomenon, but the more variables the model includes, the more difficult the model calibration and interpretation becomes. To define a criterion of selection, the hypothesis testing technique for proportions was used to decide whether the number of levels for a design variable could be reduced due to the significant probability that the proportion of level i (pi) could be equal to zero. Available data were compared using the chi square test of independence [13] in order to evaluate the null hypothesis: proportion=0.

The chi-square statistic is defined as:

$$\chi^2 = \sum_{i=1}^{k} \frac{(O_i - E_i)^2}{E_i} \qquad (1)$$

where:

O_i is the observed frequency;

E_i is the expected frequency.

If the p_i is significantly different from zero and falls in the rejection region at the 5% significance level, the null hypothesis is rejected (P-value > 0.05). Table 1 summarizes the hypothesis testing results for all the design variables defined after the first selection. Basing on the test results, some levels were deleted. For example the variable “crash location” was reduced from four levels to three levels after the test showed that the proportion of “other” (location) was not statistically significant at the 5% level. Considering, also, the uncertainty of the condition other locations, this level was not considered removing from the data set all the cases classified with “other” in the variable “Location”. In other cases, new levels were created merging previous levels in order to realize one statically significant (i.e. single accident merges falling from vehicle, run off and sudden braking).

3. Crash modeling

3.1. Logistic Regression model and interpretation

Since the response variable, CRASH SEVERITY, is a binary variable and the independent variables are categorical, the logistic regression is a suitable technique to be used because it is developed to predict a binary dependent variable as a function of predictor variables both numerical and categorical. Logistic regression is widely used in road safety studies were the dependent variable is binary, because it provide useful results:

- to predict a dependent variable on the basis of continuous and/or categorical independents and to determine the percent of variance in the dependent variable explained by the independents;
- to rank the relative importance of independents;
- to assess interaction effects;
- to understand the impact of covariate control variable.

For a binary response variable [14] the linear logistic regression model, expressed in terms of the logit transformation of the i_{th} individual’s response probability, p_i (e.g., probability of severe injury), is a linear function of the vector of explanatory variables:

$$logit(p_i) = \log\left[\frac{p_i}{1-p_i}\right] = \beta_0 + \beta_1 x_1 + \cdots + \beta_j x_j + \cdots + \beta_n x_n \qquad (2)$$

where

β_j: regression coefficients; j=1,…, n for n predictor variables x_j.

The negative sign before the linear combination of predictors produces a positive relationship between the sign of the coefficient and the direction of effect on risk. In other words, a positive coefficient represents an increase in risk and a negative coefficient represents a decrease in risk.

The logit is the natural logarithm of the odds or the likelihood ratio that the dependent variable is 1 (fatal crash) as opposed to 0 (no fatal crash). When an independent variable xi increases by one unit, with all other factors remaining constant, the odds increase by a factor exp(βi) which is called the odds ratio (OR), ranging from 0 to positive infinity. It indicates the relative amount by which the odds of the outcome (fatal) increase (OR>1) or decrease (0<OR<1) when the value of the corresponding independent variables increases by one unit.

3.2. Model Development and Results

To assess the goodness of fit for binary response models, Hosmer and Lemeshow [15] proposed a statistic test. The test assesses whether or not the observed event rates match expected event rates in “n” subgroups of the model population. The Hosmer–Lemeshow test specifically identifies n=10 subgroups sorting the observations in increasing order of their estimated event probability π_g (the deciles of fitted risk values).

Table 1. Summary of variables and statistical significance

VARIABLE	CLASSIFICATIONS	REF. VARIABLE	Code	number	proportion	P-value
ROAD TYPE	Rural road	Urban road	R	9344	0.119	0.119
	Urban road		U	69075	0.881	1.000
LIGHT CONDITION	Day time	Night	Day	61245	0.781	1.000
	Night time		Night	17174	0.219	0.219
ROAD GEOMETRY	Curve	Intersection	C	5640	0.072	0.083
	Straight road		ST	39916	0.509	1.000
	Intersection		J	31988	0.408	0.491
	Other*		OT	875	0.011	0.011*
COLLISION TYPE	Falling from vehicle*	Single accident	FV	1407	0.018	0.020*
	Run off		RO	2879	0.037	0.134
	Front/side collision		FS	56211	0.717	1.000
	Front collision*		F	181	0.002	0.002*
	Sideswipe collision		S	7433	0.095	0.283
	Obstacle collision		O	2290	0.029	0.098
	Pedestrian accident*		PA	1696	0.022	0.042*
	Sudden braking		SB	2078	0.026	0.068
	Rear – end accident		RE	4244	0.054	0.188
PTW TYPE	Moped	Motorcycle	M	26723	0.341	0.341
	Motorcycle		MC	51696	0.659	1.000
PARTNER COLLISION	Bus*	Car	B	558	0.007	0.010*
	Car		CAR	53275	0.679	1.000
	Truck		GV	4340	0.055	0.158
	Moped*		M	1190	0.015	0.038*
	Motorcycle		MC	2279	0.029	0.105
	No partner		NP	12751	0.163	0.321
	Pedestrian		P	1696	0.022	0.076
	Bicycle		B	1297	0.017	0.055
	Others*		OTH	1033	0.013	0.023*
AGE OF DRIVER (years)	14≤Age<18	25<Age<44	<18	12219	0.156	0.203
	18≤Age≤24		18-24	14627	0.187	0.555
	25≤Age≤44		25-44	34870	0.445	1.000
	45≤Age<60		45-60	13026	0.166	0.369
	≥60*		>60	3677	0.047	0.047*
CRASH CIRCUMSTANCES	Falling from vehicle	Passing	FA	2355	0.030	0.089
	Safety distance		SD	4188	0.053	0.216
	Regular driving		RE	30736	0.392	1.000
	Speed		SP	4977	0.063	0.279
	Braking*		SB_C	348	0.004	0.004*
	Inattention		I	8069	0.103	0.608
	Manoeuvring		MA	2703	0.035	0.115
	No circumstances**		NC	7613	0.097	0.505
	Yield fault		YF	5017	0.064	0.343
	Pedestrian yield fault*		PYF	1014	0.013	0.017*
	Slipping		SL	5083	0.065	0.408
	Passing		PAS	3277	0.042	0.162
	Other circumstances**		OC	2498	0.032	0.121

* Statistically insignificant at 5% level - ** Undefined factor

Based on these assumption, the Hosmer–Lemeshow test statistic is given by:

$$H = \sum_{g=1}^{n} \frac{\left(O_g - E_g\right)^2}{N_g \cdot \pi_g \cdot (1-\pi_g)} \tag{3}$$

where
O_g = observed events for the g^{th} risk group
E_g= expected events for the g^{th} risk group
N_g= observations for the g^{th} risk group
π_g= predicted risk for the g^{th} risk group.

When there is no replication in any of the subpopulations, the H statistic asymptotically follows a $\chi 2$ distribution with n-2 degrees of freedom. Large values of H (and small p-values) indicate a lack of fit of the model. As goodness of fit for the model a P-value greater than or equal to 0.10 was assumed to assess that there is no reason to reject the adequacy of the fitted model at the 90% or higher confidence level. The Wald statistic is a test which is commonly used to test the significance of individual logistic regression coefficients for each independent variable (that is, to test the null hypothesis in logistic regression that a particular logit coefficient is zero, H0: β_i =0). The Wald statistic W is the square of the ratio of the estimated value of the logistic coefficient β_i with its standard error SE(βi) and it follows a standard normal distribution under the null hypothesis that β_i =0

$$W = \left[\frac{\beta_i}{SE(\beta_i)}\right]^2 \tag{4}$$

It was observed that the Wald test often fail to reject the null hypothesis when the coefficient is significant. Therefore, the likelihood ratio test should be used in suspicious cases. The likelihood ratio can be expressed as:

G=-2 ln [(likelihood without variable)/(likelihood with variable)] (5)

Under the null hypothesis of βi =0, G follows a $\chi 2$ distribution with one degree of freedom.

The backward selection process of logistic regression was adopted in the model calibration in order to eliminate, step by step, those variables that could result not significant (i.e. P-value of Wald test higher than 0.1) and continue with testing interaction effects with only significant variables.

Since some independent variables x_i have several levels, a sub-set of dichotomous variables (dummy variables) has to be derived to represent the data in a logistic regression. It is important to understand the coding strategy in order to conduct hypothesis testing on the variables as well as to interpret their estimates. When the independent variables are characterized by a series of dichotomous variables, one of the variable is used as reference in the estimation (Table 2).

The reference variable is not represented in the model since it is defined by all 0 value in the sub-set of the design variables.

Table 2 shows the results from fitting all the explanatory variables because the backward process has not removed any variables (P-values of all the independent variables less than 0.1).

Moreover, Hosmer-Lemeshow test shows that there is no reason to reject the adequacy of the fitted model at the 90% confidence level. Finally, a graphical assessment of the fit to the logistic model developed in this study also shows that the model appears to fit the data reasonably. Figure 1 shows the plot of Pearson residuals, in which no trend can be detected.

The PTW model including all the available data for rural and urban areas showed the discriminating influence to PTW driver fatality of rural area with respect to urban area (odds ratio of 4.85). Therefore, to reach a more in deep analysis of the phenomenon, two different logit models were calibrated considering separately PTW crashes in rural and urban area.

For both the models, the P-values of all the dependent variables resulted less than 0.1, therefore the backward process has not removed any variables from the model. Hosmer-Lemeshow test shows that there is no reason to reject the adequacy of the fitted models at the 90% confidence level.

The functions g(x) for rural and urban dataset are expressed by the form of (2) with coefficients bj reported in Table 2.

From the model coefficients and odds ratio (Table 2), the following results regarding probability of a PTW crash with fatal consequences can be highlighted common to both areas:

- high speed is an important factor affecting the probability of a fatal consequences.
- crashes in daylight time are less severe than in night time;
- crashes on bending curves have higher probability of fatal consequences than accident at intersection tangents;
- single crashes have a higher probability of fatal consequences than any other collision type or partner;
- crashes involving motorcycle are more severe than crashes involving moped;
- the PTW drivers in the age classes of 25-44 years have the highest probability of fatality respect the other classes with the only exception of old drivers (age over 60).

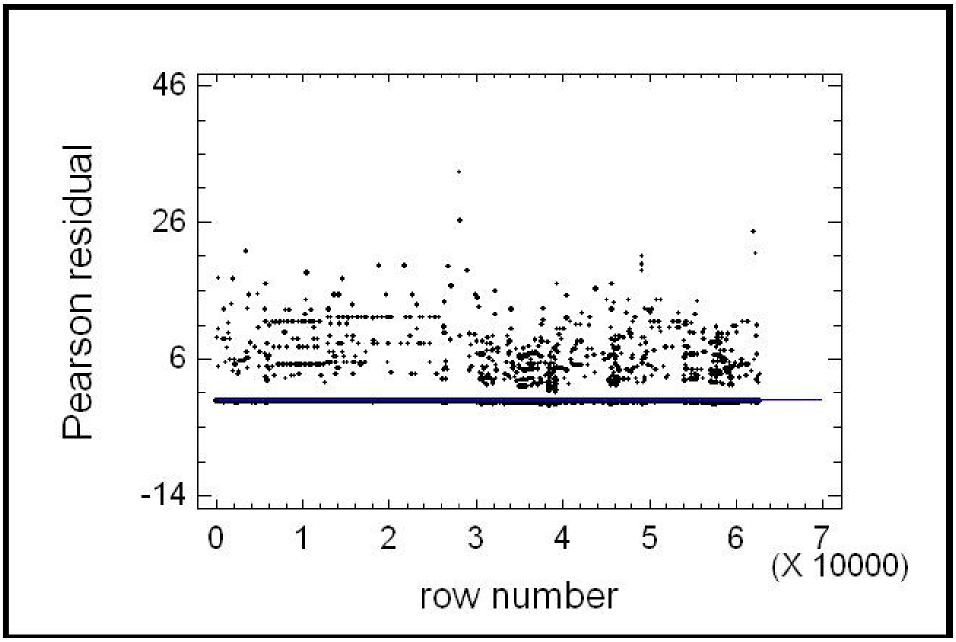

Fig. 1. Plot of Pearson residuals

Table 2. Wald Statistics, P-value and Odds ratio for the model variables

		RURAL MODEL			URBAN MODEL		
Test of Hesmer - Lemeshow		$\chi2$= 6.478 Sig = 0.594			$\chi2$= 6.943 Sig = 0.543		
VARIABLE(ID)	**REF. VAR.**	β_i	**Wald P-value**	**OR**	β_i	**Wald P-value**	**OR**
Constant (0)		-2.1	0.000	0.122	-3.694	0.000	0.025
TYPE OF ROAD							
R (1)	U						
LIGHT CONDITION							
Day (2)	Night	-0.653	0.000	0.520	-0.817	0.000	0.419
ROAD GEOMETRY			0.026			0.006	
C (3)	J	0.383	0.012	1.467	0.538	0.002	1.712
ST (4)		0.077	0.560	1.080	0.144	0.150	1.155
COLLISION TYPE			0.000			0.000	
FS (5)	SA	-0.181	0.395	0.835	-0.616	0.010	0.540
S (6)		-1.713	0.000	0.180	-1.434	0.000	0.238
O (7)		-0.384	0.293	0.681	-0.036	0.906	0.965
RE (8)		-0.798	0.008	0.450	-0.753	0.024	0.471
PTW TYPE							
M (9)	MC	-0.393	0.016	0.675	-0.541	0.000	0.582
COLLISION PARTNER			0.000			0.000	
GV (10)	CAR	0.796	0.000	2.217	1.279	0.000	3.593
NP (11)		0.702	0.005	2.018	0.192	0.270	1.211
PTW (12)		0.685	0.002	1.984	-0.280	0.281	0.756
AGE OF DRIVER			0.000			0.000	
<18 (13)	25-44	-0.817	0.002	0.442	-0.327	0.049	0.721
18-24 (14)		-0.483	0.005	0.617	-0.166	0.179	0.847
45-60 (15)		0.028	0.829	1.029	-0.046	0.719	0.955
>60 (16)		0.583	0.006	1.792	0.716	0.000	2.046
CIRCUMSTANCES			0.000				
FA (17)	PAS	-1.509	0.002	0.221	-0.985	0.035	0.374
SD (18)		-0.211	0.505	0.810	-0.491	0.180	0.612
RE (19)		-0.108	0.668	0.897	-0.038	0.885	0.962
SP (20)		0.575	0.030	1.778	1.365	0.000	3.918
IN (21)		-0.08	0.779	0.923	0.232	0.411	1.262
MA (22)		-0.049	0.886	0.952	0.405	0.211	1.499
YF (23)		-0.454	0.254	0.635	0.293	0.341	1.341
SL (24)		-0.909	0.013	0.403	0.437	0.208	1.547

Analyzing the different road surrounding environment and traffic condition, some differences of rural respecting to urban area can also be highlighted (Figure 2):

- generally collisions with a car is less severe with respect to any other partner (Good Vehicle or PTW) with the exception of collision between PTWs in rural area
- high speed remains the first contributing factors among all the variables in the class "crash typology", but passing is a high risk maneuver only in rural roads;
- inattention, Yield fault, slipping and maneuverings in the traffic are high risk circumstances above all in urban area.

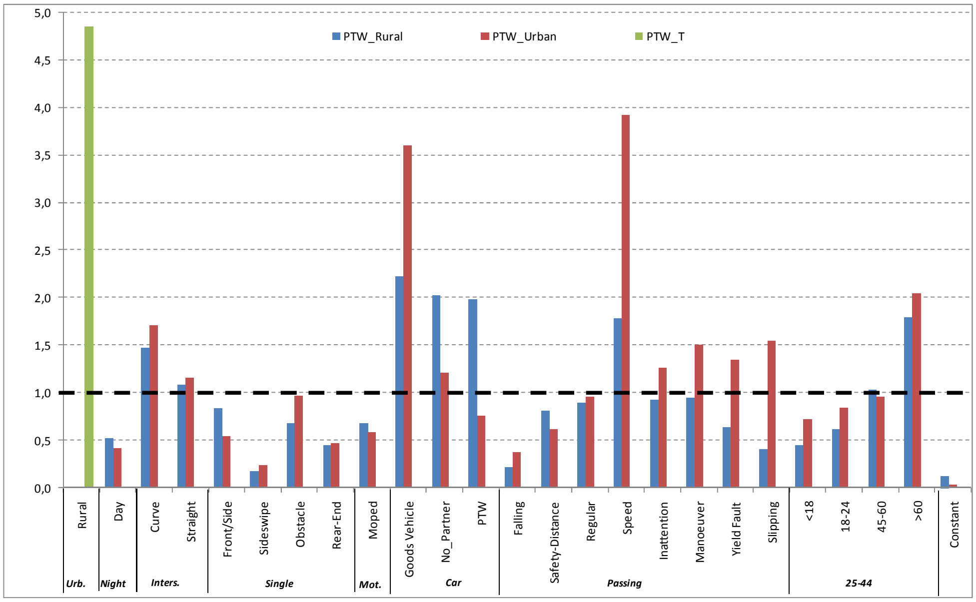

Fig. 2. Comparison of the odds ratio among the different models

4. Conclusion

Italy shows the European primacy in the number of Powered Two-Wheelers fatalities in road crashes which accounts for 30% of the total compared to the 17% of the EU average. For this reason a strong effort has to be devoted for a better understanding of the phenomenon in order to carry out effective safety policies for PTW users. In this study logistic regression is used to examine the influence of multiple factors related to road geometry, environmental condition, collision characteristics, driver attributes and type of PTW, on road crashes involving PTW in Italy. Considering the different probability of fatal consequences for PTW crashes on rural roads with respect to PTW crashes on urban streets, two different logistic models (urban, rural) were calibrated selecting the independent variable to be considered and included in the model. The Wald test and the Hosmer and Lemeshow test were performed to assess the significance of the independent variables and the goodness of fit of the models. The analysis of these models provided specific information about the contribution of the different factors to the conditional probability that PTW crash has a fatal consequences for the driver. The detailed analysis of estimated coefficients and odds ratio is reported in the paper. Some conclusions and general consideration are summarized in the following. Common factors affect the probability of a fatal crash both in rural and urban area, others have different impact to the severity of a collision. Driving at high speed results as the first circumstance of a fatal crashes if compared with other driver responsibilities or driving conditions. High speed can be considered the influencing factors to explain also other results carried out from the model:

- rural compared to urban area has a high odds ratio;
- single crashes and hit obstacles which have a higher probability of fatal consequences than the other crash typologies can be associated with free flow high speed driving;
- crashes involving motorcycle are more severe for the PTW driver than crashes involving moped which are constrained at a speed limited less than 50 km/h.

Driver's roadway perception and visibility and loss of vehicle control can be related to high severity of crash in night time and on bending curves. The high vulnerability of the PTW drivers is highlighted by the fact that among multiple vehicle collisions the more severe consequences occur when the partner of collision is a gross vehicle followed by collision with another PTW when compared with collision with a passenger car.

Analyzing the different traffic conditions between rural and urban areas, some differences of rural respecting to urban area have been highlighted by the study: passing is a high risk maneuver in rural roads and inattention, yield fault and maneuvering in the traffic are high risk circumstances above all in urban area.

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