Analysing Motorcycle Injuries on Arterial Roads in Bali using a Multinomial Logit Model

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Abstract: This paper aims to investigate the influence of accident related factors on motorcycle injuries on two arterial roads in Bali. Multinomial logit (MNL) models are estimated considering three severity classes such as slight injury, serious injury and fatal injury as response variables using local police data as explanatory variables. The analysis shows that there are four variables associated with motorcycle injuries. Sideswipe accidents involving motorcyclists were 51.7% less likely resulting in serious injuries than slight injuries. In addition, motorcycles collided with other vehicle(s), either motorist/motorcyclist failed to yield and motorcycle at fault were 89.1%, 60.7% and 44% respectively less likely resulting in fatal injuries than slight injuries. Probability analysis shows that a change in 1% of these variables could influence motorcycle injuries between 33% and 34%.

Key Words: *Road Accidents, Injury Severity, Motorcycle, Multinomial Logit*

1. INTRODUCTION

Motorcycle usage is rapidly growing in Indonesia including Bali Province. Due to the small size and the engine capacity of 100-150cc, motorcycles have higher mobility on the road. People use motorcycles for either short or long distance trips over many trip purposes including work, shopping, leisure, and education. There are two main reasons for this situation, firstly poor services of the existing public transport and secondly motorcycle is more practical to cope with traffic congestion and more efficient compared to either private cars or public transport.

The registered motorcycles in Bali annually are almost 85% of the total vehicles with an average annual growth rate of approximately 11%. In 2007 there were 1,166,694 motorcycles in Bali among the 1,377,352 total vehicles registered. In the capital city of Denpasar, the number of registered motorcycles in 2007 was 390,000 of the total of 457,000 registered vehicles. During the daytime on weekdays, number of vehicles would be doubled about 800,000 units considering commuters and students trips to and from Denpasar (Statistics of Bali Province, 2008).

Arterial roads have daily high traffic flows from which about 70% are coming from motorcycles. There are three main modes in Bali that include private cars, heavy vehicles (bus and truck) and motorcycles, and they share together the roadways including on arterial roads. No special lane is dedicated for motorcycle travel. This generates a variety of conflicts amongst the three modes quite frequently. Moreover, motorcyclists' behaviour such as speeding and manoeuvring in highly congested traffic conditions is not particularly favourable for other vehicles. This may lead to high proportion of motorcycle accidents and injuries. In fact, during period 2003-2007 there were 4489 road accidents and 8498 injuries in Bali in which almost 60% involving serious and fatal injuries. Of these road accidents, on average 70% involved with motorcycles (State Police of Bali Province, 2008). A Motorcyclist in Bali, therefore, could be regarded as a vulnerable road user. This is also in line with situation in another developing country such as Malaysia (Abdul Kadir, et.al, 2006).

Study on motorcycle accidents is essential not only to prevent them but also to reduce the injuries. This paper aims to investigate the factors influencing injuries with particular emphasis on motorcycle related injuries in Bali. As the accident factors were obtained from the local police accident reports, the analysis will be limited only to these secondary data. Two continuing arterial roads, for instance bypass Ida Bagus Mantra and bypass Ngurah Rai were chosen as the case studies.

2. LITERATURE REVIEW

2.1 Previous Studies

There have been many related studies linking between motorists and the risk of injuries (for example, O'Donnel and Connor (1996), Kockelman and Kweon (2002)). They have analysed traffic accident data using ordered multiple choice model consisting ordered logit and ordered probit models. O'Donnel and Connor (1996) found that slight increases in the probabilities of fatal or serious injuries were influenced by several factors including the increase of age's victim and vehicle speed. Other factors that may have some influence on different types of injuries include seating position, blood alcohol level, vehicle type, vehicle make and type of collision. Kockelman and Kweon (2002) found that the vehicles such as pickups and sport utility vehicles were less safe than passenger cars, especially for the accidents involving a single vehicle. However, for accidents with two-vehicle collisions it was reported that there are less severe injuries for the drivers and more severe injuries for occupants.

Another study conducted by Al-Ghamdi (2002) investigated on the influence of accident factors on fatal and non fatal accidents in Saudi Arabia. The study findings showed that accident location and cause of accident are significantly associated with a fatal accident. Accident factors used in the study include accident location, accident type, collision type, time of accident, cause of accident, driver age at fault, vehicle type, nationality and license status. Some of the accident factors classifications of that study are used as the independent (predictor) variables in the analysis.

There were few studies, however, regarding motorcycle injuries particularly in developing countries. A Study has been conducted on motorcycle injury and vehicle damage severity in Singapore using ordered probit models (Quddus, et al., 2002). The study found that the factors that lead to increase in probability of severe injuries include motorcyclists who were non-Singaporean nationality, increased engine capacity, headlight not turned on during daytime,

collisions with pedestrians and stationary objects, driving during early morning hours, having a pillion passenger, and motorcyclist is at fault for the accident. Factors leading to the increase in probability of vehicle damage included some similar factors as above together with some differences including less damage associated with pedestrian collisions and female drivers. It was also found that both injury severity and vehicle damage severity levels were decreasing over time. There are some significant differences between motorcyclists in developing and developed countries regarding their motorcycle usage. For instance, pillion passengers are very uncommon in western countries. In addition, motorcycles in developing countries are used mainly for commuting and utilitarian trips as opposed to recreational trips (Quddus, et.al, 2002).

Other related studies discussed the issues on helmet and motorcycle accidents and injuries. They have been investigated by Ichikawa, et al. (2003) in Thailand, Skalkidou et al. (1999) in Greece, and Keng (2005) in Taiwan. Those studies used ordered multiple choice models to conduct the investigations. The ordered multiple choice models have also been conducted in this study to carry out the statistical analyses for the motorcycle injuries. The results indicated no ordinal nature in categories. In this study, therefore, Multinomial Logit model is employed with the assumption that the categorical outcomes have no ordinal nature.

2.2 Multinomial Logit Model

The objective of the Multinomial Logit (MNL) model is to estimate a function that determines outcome probabilities. This study uses MNL model to investigate the relationships that exist between accident factors and motorcycle injuries with attention to fatal, serious or slight injuries on two arterial roads in Bali. The probability of a motorcycle injury is restricted to lie between zero and one. Multinomial logistic regression is used for a dependent variable with unordered categories. One category is chosen as the reference category, typically the first, the last or the value with the lowest or the highest frequency. The probability of each category is compared to the probability of reference category. For categories i = 2….K, the probability of each category is as follows (Borooah, 2001):

$$\Pr(Y = i) = \frac{\exp(Z_i)}{1 + \sum_{h=2}^{K} \exp(Z_{hi})} \tag{1}$$

Where: $\alpha_i + \sum_{h=1}^{H} \beta_{ih} x_{ih} = Z_i$.

For the reference category,

$$\Pr(Y = 1) = \frac{1}{1 + \sum_{h=2}^{K} \exp(Z_{hi})} \tag{2}$$

After rearranging equation (1) and (2), the MNL model can be written as follows:

$$\mathrm{Ln}\left(\frac{P(Y = i)}{P(Y = 1)}\right) = \alpha_i + \sum_{h=1}^{H} \beta_{ih} x_{ih} = Z_i \tag{3}$$

Where:

i	:	the number of injury categories
β_{ih}, X_{ih}	:	vectors of the estimated parameters and predictor variables respectively
$\frac{P(Y = i)}{P(Y = 1)}$	:	the probability of motorcycle injuries either fatal, serious injury or slight injury with the first category as reference.

The equation above expressed the logit (log odds) as a liner function of the independent factors (Xs). Therefore, equation (3) allows for the interpretation of the logit weights for variables in the same way as in linear regressions.

3. CASE STUDY AREA AND DATA DESCRIPTION

3.1 Case Study Area

Province of Bali has an area of 5,634.40 km^2. The population there is about 3.4 million. The capital city Denpasar is located in the Southern Bali. The island is widely known as a tourist destination. Most of popular tourist destinations are located in southern areas including Kuta, Sanur, and Nusa Dua. Therefore, these areas are the most densely populated areas than the other parts of Bali.

At present, total arterial road length in Bali is 199.63 km. Two of these arterial roads are bypass Ida Bagus Mantra and bypass I Gusti Ngurah Rai. Bypass Ida Bagus Mantra has been in operation since 2003 and is about 23 km long connecting between Kusamba (in eastern Bali) and Tohpati. Bypass Ngurah Rai connects between Tohpati and Nusa Dua spanning about 30 km and has been in operations since 1981. Bypass I Gusti Ngurah Rai is a dual carriageway which has a median, while bypass Ida Bagus Mantra is a single carriageway which has no median. The continuing arterial roads are shown in black lines in Figure 1.

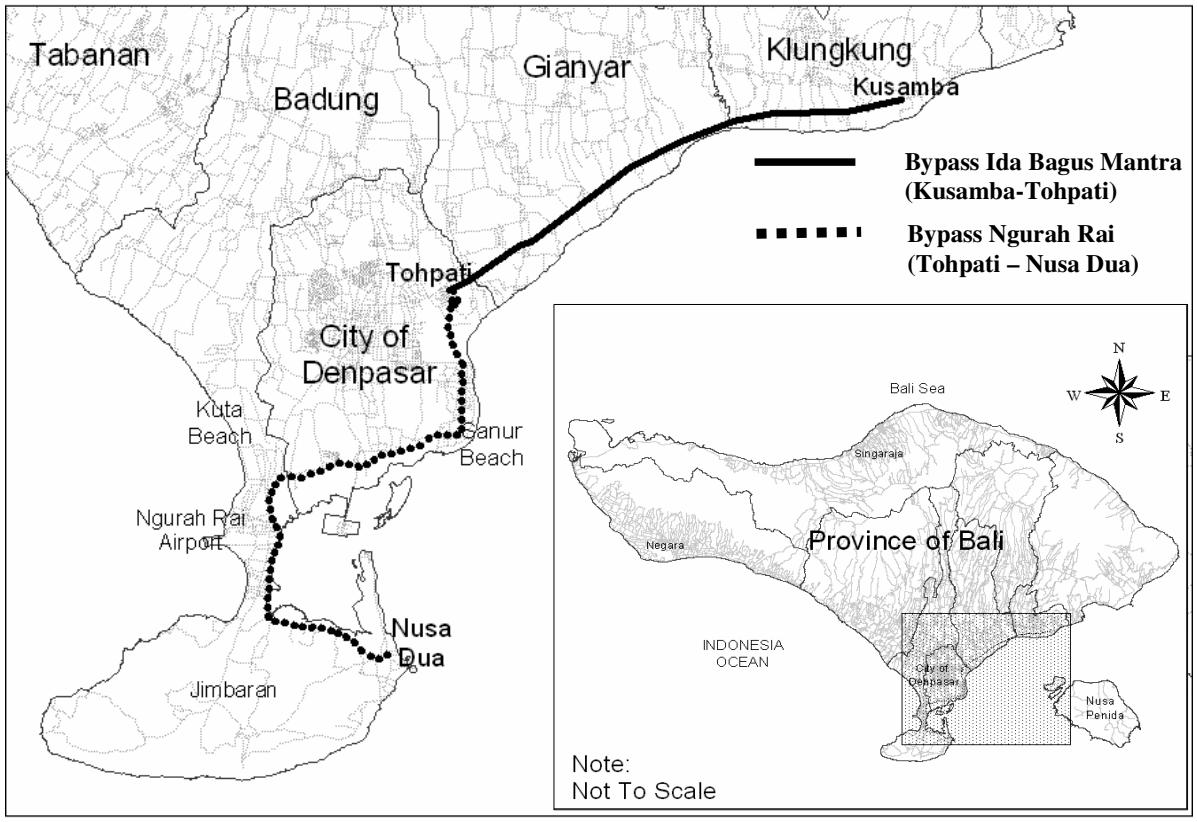

Figure 1 Case study area

3.2 Data Description

Figure 2 represents road accidents and motorcycle accidents happened during 2004-2007 on the two arterial roads, bypass Ida Bagus Mantra and bypass I Gusti Ngurah Rai. Figure 2 shows that the gradual increase accidents from 2004 to 2005 and from 2006 to 2007. The number of accidents, however, has been increased dramatically from 2005 to 2006 by more than 2 folds. During 2005-2006, it was also recorded as the period of the highest increase in motorcycle ownership in Bali. These increase accidents may be described as a result of increase of traffic volume along these two roads. From figure 2, it is also shown that in average motorcycle accidents were accounted for 74% of total accidents on these roads during period 2004-2007.

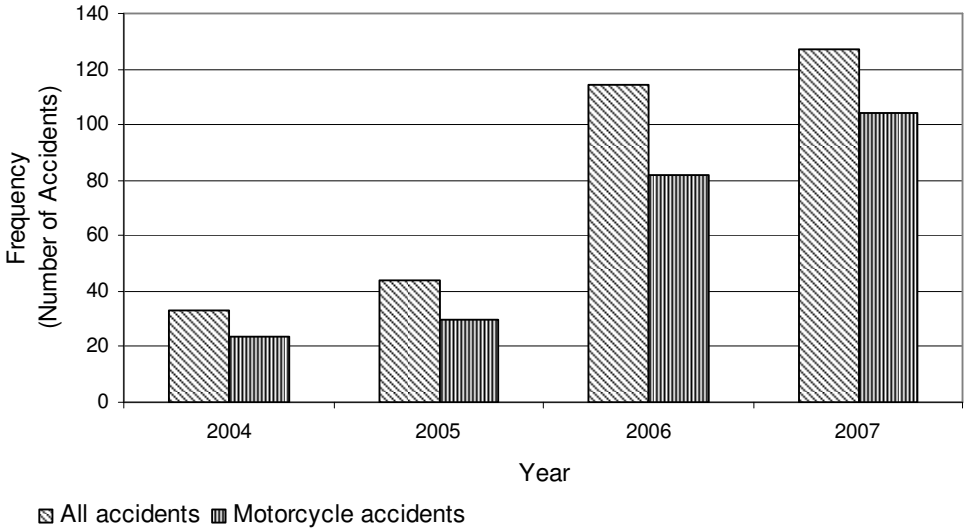

Figure 2 Road accidents and motorcycle accidents

Table 1 shows motorcycle injuries and road injuries (including all modes) considering three severity classes such as fatal (killed), serious and slight injuries, during 2004-2007 on the two arterial roads. Accordingly, motorcycle KSI (Killed or Serious Injuries) has approximately 76% of those all motor vehicle based KSI injuries.

Based on Table 1, motorcycle injuries on bypass Ida Bagus Mantra have different patterns with those on bypass I Gusti Ngurah Rai. The former has number of fatal injuries far smaller than slight injuries while on the latter has number of fatal injuries much higher than slight injuries. As a result, the total number of motorcycle fatal and slight injuries on the two arterial roads is somewhat similar. This pattern, in general, would follow the accident pattern as shown in Figure 3.

Table 1 Injuries data on bypass Ida Bagus Mantra and bypass Ngurah Rai

	All motor vehicles		Motorcycles	
	Bypass IB Mantra	Bypass Ngr Rai	Bypass IB Mantra	Bypass Ngr Rai
Fatal Injury	73	99	54	79
Serious Injury	117	96	89	71
Slight Injury	133	86	76	59
Total	323	281	219	209

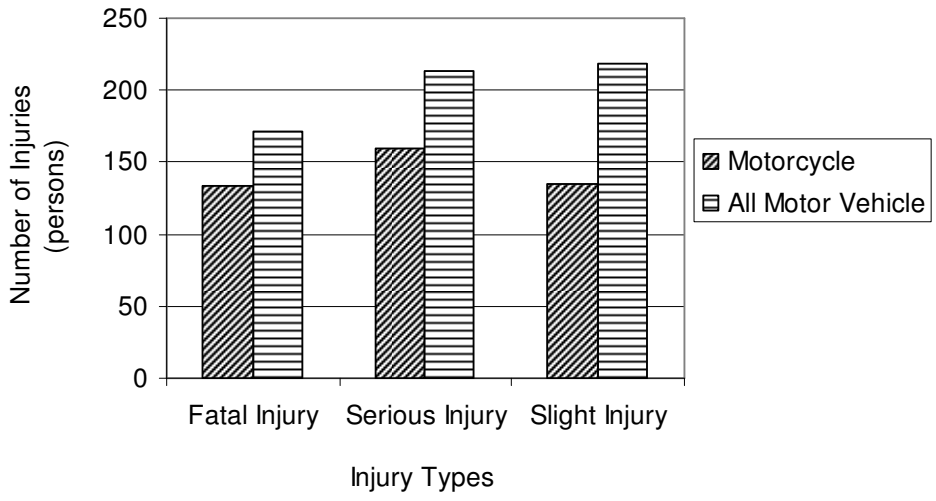

Figure 3 Road injuries and motorcycle injuries

4. MODEL DEVELOPMENT

Data availability has been primary considered in determining predictor variables for this study. All variables mentioned in Table 2 were available from the police. Other important factors including wearing helmets and speed at accidents, however, were not available in the database.. Therefore, the variables such as wearing helmet and speed at accidents were not included in the model development. Even so the database contains the data related to accident causes, for instance accidents occurred due to high speed of motorists (called as speeding). Therefore, speeding was included as a predictor variable in the model development. This study attempted to consider all relevant factors which influencing motorcycle injuries, despite the shortcoming of existing accident data in Bali.

Some of accident related variables (Table 2, variable type no. 2 through no.7), were considered as the predictor variables in this study following those used in a study conducted by Al-Ghamdi (2002). Age and gender have long been a high priority in accident risk assessment (Al-Ghamdi, 2002, Kockelman and Kweon, 2001, O'Donnel and Connor, 1996). In addition, age has been indicated to have non-linear effects, for example in a form of a quadratic expression, with the response variable (Al-Ghamdi, 2002). Therefore, age, squared-age and gender (of driver/motorcyclist at fault) were considered as predictor variables.

Response variable (injuries) in this study is nominal in nature. All independent variables are categorical, but age and squared-age, which are continuous variables. In order to represent categorical variables, dummy variables are created following the coding system in SPSS, software used in this study. Study variables and their codes are shown in Table 2.

Table 2 Study variables

No.	Variable Type	Description	Variable Title
1.	Injuries	0 = Slight Injury 1 = Serious Injury 2 = Fatal Injury	Injuries
2.	Accident type	1 = with fixed object, 2 = otherwise 1 = overturned, 2 = otherwise 1 = with vehicles, 2 = otherwise	Atyp1 Atyp2 Atyp3
3.	Collision type	1 = Out of Control, 2 = otherwise 1 = Right Angle, 2 = otherwise 1 = Side Swipe, 2 = otherwise 1 = Rear End, 2 = otherwise 1 = Head On, 2 = otherwise	Ctyp0 Ctyp1 Ctyp2 Ctyp3 Ctyp4
4.	Vehicle type (at fault)	1 = Heavy vehicle, 2 = otherwise 1 = Light vehicle, 2 = otherwise 1 = motorcycle, 2 = otherwise	Veh0 Veh1 Veh2
5.	Accident cause	1 = Other, 2 = otherwise 1 = Speeding, 2 = otherwise 1 = Run red light, 2 = otherwise 1 = Follow too close, 2 = otherwise 1 = Wrong way, 2 = otherwise 1 = Failed to yield, 2 = otherwise	Caus0 Caus1 Caus2 Caus3 Caus4 Caus5
6.	Accident Location	1 = Link 2 = Junction	Loc
7.	Time of accident	1 = Day time 2 = Night time	Time
8.	Gender of driver/motorcyclist at fault	1 = Male 2 = Female	Gender
9.	Age of driver/ motorcyclists at fault	Year	Age
10.	Squared Age of driver/motorcyclist at fault	Year	Age Sqr

Looking at the data proportion shown in Table 3, some predictor variables can be neglected because of their small proportion. The hypothesis testing technique for proportions was used in this study to decide whether a classification could be reduced. The following typical test was used:

$$H_0: p_i = 0$$
$$H_a: p_i \neq 0$$

Where, p_i is the proportion of a variable.

Based on the test, there were four variables excluded from the model development stage, for instance accidents with fixed object, accident because of speeding, run red light, and heavy vehicle at fault.

Table 3 Hypothesis testing

Description	X	N	P-value	95% Confidence level	
				Lower	Upper
Accident Type					
With fixed object *	11	428	0.026	0.0	0.1
Overturned	37	428	0.086	0.1	0.1
With vehicles	380	428	0.888	0.9	0.9
Collision Type					
Out of Control	58	428	0.136	0.1	0.2
Right Angle	101	428	0.236	0.2	0.3
Side Swipe	52	428	0.121	0.1	0.2
Rear End	104	428	0.243	0.2	0.3
Head On	113	428	0.264	0.2	0.3
Vehicle Type (at fault)					
Heavy vehicle*	31	428	0.072	0.0	0.1
Light vehicle	109	428	0.255	0.2	0.3
Motorcycle	288	428	0.673	0.6	0.7
Accidents Cause					
Others	68	428	0.159	0.1	0.2
Speeding*	14	428	0.033	0.0	0.0
Run red light*	6	428	0.014	0.0	0.0
Follow too close	103	428	0.241	0.2	0.3
Wrong way	135	428	0.315	0.3	0.4
Failed to yield	102	428	0.238	0.2	0.3
Gender (at fault)					
Male	369	428	0.862	0.8	0.9
Female	59	428	0.138	0.1	0.2
Location					
Link	357	428	0.834	0.8	0.9
Junction	71	428	0.166	0.1	0.2
Time of accident					
Day time	216	428	0.505	0.5	0.6
Night time	212	428	0.495	0.4	0.5

* Statistically insignificant at the 5% level (the 95% confidence limits include 0)
where:
X = number of occurrence (yes =1)
N = sample size

The backward elimination process of multinomial logistic regression was followed using SPSS ver.15. All of reduced variables were selected using Likelihood Ratio (LR) Chi-Square test calculated by -2*[L(null model) - L(fitted model)]. Each removed variable that gives the value of LR test more or equal to the value LR test when all variables included were eliminated from the model. As a result, 13 variable classifications were excluded from the model as shown in Table 4.

Table 4 Variables elimination

Model	Action	Effect(s)	Model Fitting Criteria	Effect Selection Tests		
			-2 Log Likelihood	Chi-Square(a)	df	Sig.
0	Entered	<all>(b)	647.141	.		
1	Remove	Ctyp4	647.141	.000	0	.
2	Remove	Caus3	647.264	.122	2	.941
3	Remove	Time	647.596	.332	2	.847
4	Remove	Veh1	647.926	.331	2	.848
5	Remove	Age	648.654	.727	2	.695
6	Remove	AgeSqr	648.743	.089	2	.956
7	Remove	Ctyp1	649.751	1.008	2	.604
8	Remove	Ctyp0	650.875	1.124	2	.570
9	Remove	Caus0	652.388	1.513	2	.469
10	Remove	Atyp2	654.452	2.065	2	.356
11	Remove	Ctyp3	656.610	2.158	2	.340
12	Remove	Loc	659.512	2.902	2	.234
13	Remove	Caus4	662.636	3.124	2	.210

Where

1. Ctyp4 = Head on collisions
2. Caus3 = Follow too close
3. Time = Time of accidents
4. Veh1 = Light vehilce
5. AgeSqr = Squared Age
6. Ctyp1 = Right angle collisions
7. Age = Age of driver/motorcyclists at fault
8. Ctyp0 = Out of control collisions
9. Caus0 = Accidents due others
10. Atyp2 = With vehicles
11. Ctyp3 = Rear end Collisions
12. Loc = Location of accidents
13. Caus4 = Wrong way

With reference to Washington et al. (2003) mentioned that in multinomial choice models, the higher pseudo R^2 (goodness of fit), the better the model. However, this is not always true. O'Donnel and Connor (2002) stated that it is usual practice to ignore such measures because there are no generally accepted measures for these types of models and have empirical and theoritical upper limits which are sometimes substantially less than one. Instead, measures to determine the model accuracy are presented below.

The presence of the relationship between the dependent variable and combination of independent variables are based on the statistical significance of the final model chi-square based on Table 5. In this analysis, the probability of the model chi-square (58.444) was 0.000, less than or equal to the level of significance of 0.05. The null hypothesis is that there was no difference between the model without independent variables and the model with independent variables was rejected. In other words, there exists a significant relationship between the independent variables and the dependent variable.

The classification accuracy rate typically should be 25% or more, higher than the proportional by chance accuracy rate. The proportional by chance accuracy rate was computed by calculating the proportion of each injury severity class. It was computed by summing $0.315^2 + 0.374^2 + 0.311^2$ which is equal to 0.336 (34%). The overall classification accuracy rate was 47.7% which was greater than the proportional by chance accuracy criteria of 42% (1.25 x 34.0% = 42%). Therefore, the criteria of classification accuracy is satisfied (refer Table 5).

Table 5 Classification accuracy

Model Fitting Information				
Model	Model Fitting	Likelihood Ratio Tests		
	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	721.080			
Final	662.636	58.444	10	.000
Data Proportions				
		N	Marginal Percentage	
Injuries	Slight Injury	135	31.5%	
	Serious Injury	160	37.4%	
	Fatal Injury	133	31.1%	
Classification Accuracy				
Observed	Predicted			
	Slight	Serious Injury	Fatal Injury	Percent
Slight Injury	33	70	32	24.4%
Serious Injury	24	93	43	58.1%
Fatal Injury	17	38	78	58.6%
Overall Percentage	17.3%	47.0%	35.7%	47.7%

5. RESULTS AND DISCUSSIONS

In this study, the dependent variable is motorcycle injury considering three severity classes: slight (SC1), serious (SC2), and fatal (SC3). The slight injury is considered as the reference or the base category. Estimated coefficients measure the change in the logit for a one-unit change in the predictor variable while keeping the other predictor variables constant. A positively estimated coefficient implies an increase in the likelihood that an injury will occur within serious or fatal classes. A negative estimated coefficient indicates that there is less likelihood that an injury will occur within serious or fatal classes. P-value indicates whether or not a change in the predictor variable significantly changes the logit at the acceptance level. If p-value is greater than the accepted confidence level, then there is insufficient evidence that a change in the predictor variable affects the response category with respect to the reference category.

Discussions are focused on accidents related factors which have 95% significance of motorcycle injuries based on the model results as shown in Table 6. Table 6 shows the statistically significant predictor variables obtained from the analysis. As shown in Table 6, multicollinearity in the multinomial logistic regression model is not present. This is detected by examining the standard errors (Std) for the β coefficients in which none of them was larger than 2.0.

Table 6 Model results

Variables	Coef (β)		Std. Errors	p-value	Exp(β)
Constant [SC1]	0		--	--	
Constant [SC2]	0.574		0.727	0.430	
Constant [SC3]	**2.981**	***	0.688	0.000	
Atyp3 [SC2]	**-0.964**	*	0.602	0.109	0.381
Atyp3 [SC3]	**- 2.213**	***	0.570	0.000	0.109
Ctyp2 [SC2]	**-0.728**	***	0.363	0.045	0.483
Ctyp2 (SC3)	**-0.775**	**	0.407	0.057	0.461
Caus5 [SC2]	0.065		0.276	0.813	1.068
Caus5 [SC3]	**-0.934**	***	0.342	0.006	0.393
Gender [SC2]	**0.705**	**	0.379	0.063	2.024
Gender [SC3]	-0.408		0.358	0.255	0.665
Veh2 [SC2]	-0.044		0.259	0.865	0.957
Veh2 [SC3]	**-0.579**	***	0.279	0.038	0.560
No. of Observations = 428					
Pseudo R^2 (Mc Fadden) = 0.062					
Pseudo R^2 (Nagelkerke) = 0.144					

Notes:
0 in Coef. column indicates a constant term set to zero
SC1, SC2 and SC3 in parentheses denote Slight Injury, Serious Injury and Fatal Injury
Bold figures are significant as follows:
*** Significant at 95%, ** Significant at 90% , * Significant at 80%.

The value of Exp(β) for sideswipe accidents (ctyp2) on motorcycle serious injury (SC2) was 0.483 which implies that the odds decreased by 51.7% (0.483 - 1.0 = -0.517). Hence, sideswipe accidents involving motorcyclists were 51.7% less likely to influence motorcycle serious injury than slight injury. Table 6 also shows that motorcycle collided with other vehicle(s) (atyp3), either motorist or motorcyclist failed to yield (caus5) and motorcycle at fault (veh2) were negatively related to motorcycle fatal injury (SC3). They were 89.1%, 60.7% and 44% respectively less likely to influence motorcycle fatal injury than slight injury. The large constant for SC3 indicated that there will be some other factors, for instance road infrastructure or road surface condition related factors that may be impacted on motorcycle fatal injuries.

The log of the odds for the serious injury (SC2) and fatal injury (SC3) are calculated by multiplying the coefficients for the first and second group from the table of parameter estimates times the variables:
SC2 = 0.574-0.964*Atyp3-0.728*Ctyp2 _+0.065*Caus5+0.705*Gender-0.044*vehicle2
SC3 = 2.981-2.213*Atyp3-0.775*Ctyp2 _-0.934*Caus5 -0.408*Gender-0.579*vehicle2

Having computed the log of the odds for each group, the log of the odds is converted to a probability number with the following formulas:

P(slight injury)= $\frac{1}{e^{(SC2)}+e^{(SC3)}+1}$; P(serious injury)= $\frac{e^{(SC2)}}{e^{(SC2)}+e^{(SC3)}+1}$; and

P(fatal injury)= $\frac{e^{(SC3)}}{e^{(SC2)}+e^{(SC3)}+1}$.

Where: $e^{(SC1)} = e^{(0)} = 1$.

Suppose there is a 1% change in sideswipe accidents involving motorcycle so other variables are being held constant, giving that SC2 = -0.964*Atyp3 = -0.964*0.01 = -0.00964 and SC3 = -2.213*0.01 = -0.02213. The percentage change (probability) of each injury will give P(serious injury) = 33.4%, P(fatal injury) = 32.9% and P(slight injury) = 33.7%. The probability of each injury based on the rest three significant variables is summarised in Table 7.

Table 7 The probability of motorcycle injuries

No.		% Change in Injuries		
		Slight Injury	Serious Injury	Fatal Injury
1.	Change in 1% Atyp3	33.4%	32.9%	33.7%
2.	Change in 1% Ctyp2	33.3%	33.2%	33.5%
3.	Change in 1% Caus5	33.5%	33.1%	33.4%
4.	Change in 1% Veh2	33.4%	33.2%	33.4%

Where
Atyp3 = With vehicles
Ctyp2 = Sideswipe
Caus5 = Failed to yield
Veh2 = motorcycle (at fault)

Table 7 shows that 1% change in sideswipe accidents involving motorcyclists, motorcycle collided with other vehicle(s), either motorist or motorcyclist failed to yield and motorcycle at fault influenced motorcycle injuries between 33% and 34%.

With regard to motorcycle accidents with other vehicle(s) and sideswipe accidents are probably explained by the fact that in typical mixed traffic, motorcycles shared the roadways together with heavy and light vehicles and no special lane provided for motorcycle, so motorcycles were the most vulnerable ones. Motorist/motorcyclist failed to yield is such a common view in Bali due to the ignorance of motorists to comply with road and traffic regulation. Strict reinforcement on issuing driving license by the local police is needed to cope with such behaviours. This may also apply to reduce motorcyclist at fault.

6. CONCLUSIONS

This study develops a multinomial logit model to investigate the influence of accident factors on motorcycles injuries. The risk analyses show that sideswipe accidents involving motorcyclists were 51.7% less likely resulting serious injury than slight injury. Meanwhile, motorcycle collided with vehicles, either motorist/motorcyclist failed to yield and motorcycle at fault were 89.1%, 60.7% and 44% respectively less likely resulting in fatal injury than slight injury.

The probability analyses present that 1% change in sideswipe accidents involving motorcyclists, motorcycle collided with vehicles, either motorist/motorcyclist failed to yield and motorcycle at fault could influence motorcycle injuries on average between 33% and 34%. Introducing road safety strategy that is paying more attention on these significant factors should be given as a top priority by local government. By reducing one accident factor may also have an impact to others. For instance, introducing awareness for reduction in failed to yield violation at the same time may also decrease sideswipe accident.

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