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FACTORS AFFECTING BICYCLE FATAL AND SERIOUS INJURY CRASHES IN VICTORIA, AUSTRALIA

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ABSTRACT

Bicyclists are among vulnerable road users, so the bicyclists' safety on the road network has been one of the main concerns of researchers and authorities in the last decade. Each year, an average of 35 cyclists are killed and over 2500 cyclists are seriously injured in Australia. Between 2011 and 2013, in Australia, 120 fatalities were cyclists. Therefore, it is necessary to understand the bicyclists' serious casualty problem in order to reduce the risk of fatality and serious injury crashes on the road network. This study utilized logistic regression modelling technique to understand the factors affecting fatal/serious injury compared to minor and non-injury bicycle crashes in Victoria, Australia from 2004 to 2013. It examined the effects of human characteristics (i.e. age, gender and helmet use), road characteristics (i.e. road classification, road alignment and intersection type), environmental characteristics (i.e. weather condition) and crash characteristics (i.e. crash time and crash spatial characteristics) on severity of bicycle crashes. The results of this study showed that crash time, bicyclist's age, helmet use, speed zone, lighting condition, bicyclist's intent, other road user's intent and traffic control for other road user's approach were the significant variables affecting crash severity of two-vehicles in which at least one bicyclist was involved. This study provided a better understanding of the factors contributing to bicycle serious casualty problem to design and implement safer infrastructure on Victoria's road network. The results of this study would also help to prioritize bicycle crash countermeasures more efficiently and to identify the most appropriate solutions for bicycle crash issues in Victoria, Australia.

1. RESEARCH BACKGROUND

Recently, many road authorities have been developed policies and programs to increase active transport commuters (bicyclists and pedestrians) in the road network. The main reason is to reduce traffic congestion and air pollution in order to increase the level of public health. However, bicyclists and pedestrians are among vulnerable road users and to promote active transport, road infrastructure should be improved to ensure that a safe environment is provided to bicyclists and pedestrians. Bicyclists' safety in the road network has been a main concern of researchers and authorities in the last decade (Poulos et al. 2015; Sanders, 2015). Each year, an average of 35 cyclists are killed and over 2500 cyclists are seriously injured in Australia (Australian Transport Safety Bureau, 2006). Therefore, it is necessary to understand the bicyclists' serious casualty problem in order to reduce fatal and serious injury crashes on the road network.

Review of the literature on factors affecting bicycle crashes showed that many studies utilized crash databases to understand the effect of road, environment, vehicle and human demographics factors on number and severity of bicycle crashes on road network (Klop and Khattak 1999; de Lapparent 2005; Loo and Tsui 2010; Moore et al. 2011; Pai 2011; Chen et al. 2012; Kim et al. 2012; Martínez-Ruiz et al. 2013; Hu et al. 2014; Kaplan et al. 2013; Lawrence et al. 2015; Bai et al. 2015).

In Australia, two recent studies were conducted to understand crash attributes affecting bicycle crash severity (Boufous et al. 2013, Lawrence et al. 2015). These studies utilized Victoria crash database. Boufous et al. (2013) investigated the difference between single and multi-vehicle bicycle road crashes in Victoria. Both police records and hospital admission data for 2004 to 2008 were used in this study. Analysing the police record in this study showed that single bicycle crashes were more likely to happen in dark and in wet condition and in rural areas. They also found that single bicycle crashes were as severe as multi vehicle crashes using hospital data. While previous studies showed that single bicycle crashes are less severe. This is due to considering both off-road and on-road crashes in previous studies. Lawrence et al. (2015) examined the spatial trends in cycling-related injury in Melbourne metropolitan areas. Kernel density estimation model, as well as GIS, were used to find the injury density from 2000 to 2011.

All these studies improved the understanding of crash parameters affecting the number and severity of bicycle crashes so that some useful countermeasures could be designed to reduce the bicyclist injury problem. However, very few studies were conducted in Australia. Furthermore, recently, Australian road authorities have adopted a Safe System approach on Australian road network. The main long term objective of this approach is to eliminate fatal and serious injury crashes from Australian road network. So, investigating factors influencing bicyclist's fatal and serious injury (FSI) crashes, rather than all casualty crashes, takes an important priority. Therefore, it is necessary to carry out an analysis of factors influencing bicycle serious casualty problem in Australia.

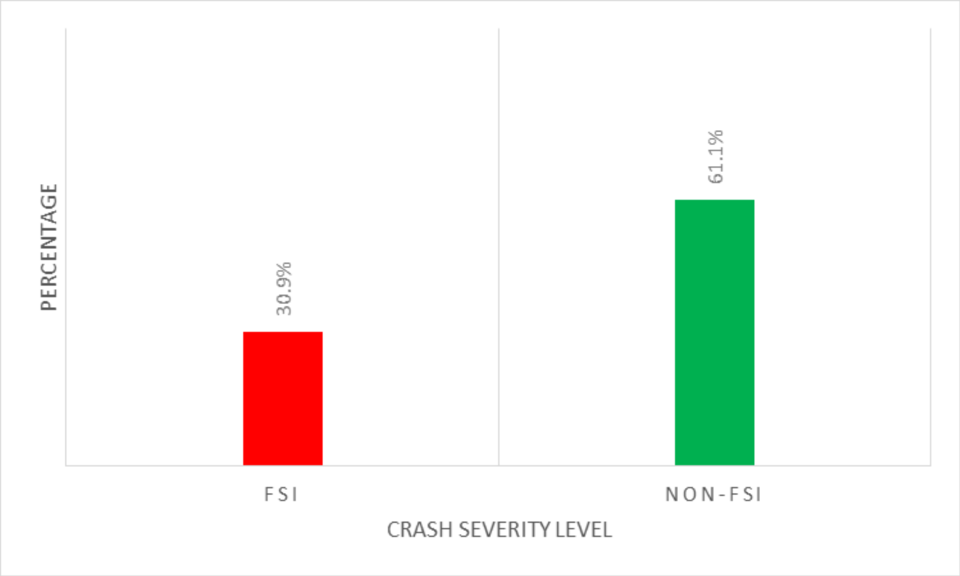
This study examines the effects of road and environment characteristics, as well as human and vehicle characteristics, on the severity of bicycle crashes in Victoria, Australia.

The next section of this paper outlines the database used in this study. Then, the data analysis method, which was utilized to understand the crash attributes affecting bicycle crash severity, is explained. This is followed by discussion of results and conclusions.

2. DATA

Victorian crash data was utilized in this study. This database included crash characteristics, vehicle features, collision types, road user characteristics, etc. All two-vehicle crashes, including at least one bicycle, were extracted from the main database. The final extracted database included bicycle crashes which were took place in Victorian road network between 2004 and 2013. The total number of vehicle-bicycle crashes for these ten years was 11336. FSI crashes accounted for 30.7% (3483) of total number of crashes. The Victorian database contains all crashes in which one vehicle, two vehicles or multiple vehicles are involved. Two-vehicle crashes were considered in this study. Figure 1 presents the distribution of bicycle crash severity in the data.

Figure 1: Distribution of bicycle crash severity levels



3. DATA ANALYSIS METHOD

Previous section described the data that was used in this study. This section explains the statistical methods which were utilized to analyse the data.

In this study, the dependent variable is "crash severity" which indicates whether or not the bicycle crash severity was FSI. In this study, a two-step analysis is carried out.

1. In the first step, a series of Chi-Square test is performed to find the independent variables (see Table 1) influencing the dependent variable ("crash severity" variable). The Chi-Square test is carried out using Pearson Chi-Square test of association (Levine et al. 2008).

2. The dependent variable in this study is "crash severity" which is a binary variable. Therefore, a Binary Logistic Regression model was developed in order to explore the relative importance of the significant variables. This method was also considered by other researchers to understand factors influencing severity of bicycle crashes (Loo and Tsui, 2010; Bai et al. 2015; Hu et al. 2014)

Table 1: Variables considered in this study

Variables	Variable levels
Other vehicle's intent	1:Going straight ahead; 2:Turning right; 3:Turning left; 4:Leaving a driveway; 5:'U' turning; 6:Changing lanes; 7:Overtaking; 8:Merging; 9:Reversing; 10:Parking or unparking; 11:Parked legally; 12:Parked illegally; 13:Stationary accident; 14:Stationary broken down; 15:Other stationary; 16:Slow/stopping; 17:Out of control; 18:Wrong way; 19:Not known
Bicyclist's intent	1:Going straight ahead; 2:Turning right; 3:Turning left; 4:Leaving a driveway; 5:'U' turning; 6:Changing lanes; 7:Overtaking; 8:Merging; 9:Reversing; 10:Parking or unparking; 11:Parked legally; 12:Parked illegally; 13:Stationary accident; 14:Stationary broken down; 15:Other stationary; 16:Slow/stopping; 17:Out of control; 18:Wrong way; 19:Not known

Variables	Variable levels
Traffic control (other vehicle's approach)	1:No control; 2:Stop go or Flashing lights; 3:Ped Light or Ped Crossing; 4:Roundabout; 5:Give way or stop sign; 6:Other; 7:Unknown
Traffic control (bicyclist's approach)	1:No control; 2:Stop go or Flashing lights; 3:Ped Light or Ped Crossing; 4:Roundabout; 5:Give way or stop sign; 6:Other; 7:Unknown
Location type	If location type was intersection =1, Otherwise =0
Bicyclist's age	1: <=14; 2: 15-17; 3: 18-25; 4: 26-45; 5: 46-65; 6: >65
Speed zone	1: 40km/hr; 2: 50km/hr; 3: 60km/hr; 4: >=75km/hr; 5: Other; 6: Not Known
Crash time	1:Dark AM (00:00AM-6:00AM); 2:Mornign Peak (6:00AM-9:00AM); 3:Morning Off Peak (9:00AM-4:00PM); 4:Afternoon Peak (4:00PM-7:00PM); 5:Afternoon Off-Peak (7:00PM-11:59PM)
Road geometry	1:cross intersection; 2:'T' Intersection; 3:Other intersection; 4:Not at intersection; 5:Other
Helmet use (bicyclist)	1:Crash helmet worn; 2:Crash helmet not worn4; 3:Not appropriate; 4:Not known
Road surface (bicyclist's approach)	1:Paved; 2:Unpaved; 3:Gravel; 4:Not known
Road surface (other vehicle's approach)	1:Paved; 2:Unpaved; 3:Gravel; 4:Not known
Lighting condition	1:Day; 2:Dask/Dawn; 3:Dark; 4:Unknown
Melbourne/greater Melbourne/others	1:Melbourne; 2:Greater Melbourne; 3:Others
Bicyclist's gender	1:Male; 2:Female; 3:Unknown

In the first step, Pearson Chi-Square test was conducted to identify the crash attributes which significantly affected the dependent variable.

The chi-square statistic compared the tallies or counts of categorical responses between two (or more) independent groups. There were several types of chi-square tests depending on the way the data was collected and the hypothesis being tested (Levine et al. 2008). In this study, chi-square test was utilized to test the association of two categorical variables.

For a contingency table that has r rows and c columns, the chi-square test could be thought of as a test of independence. In a test of independence, the null and alternative hypotheses were:

H_o: The two categorical variables are independent.

H_1: The two categorical variables are related.

Equation (1) was used for computing the value of chi-square statistics.

$$\chi 2 = \sum \frac{(f_o - f_e)^2}{f_e} \quad (1)$$

Here f_o was the frequency of the observed data and f_e was the frequency of the expected values (Levine et al. 2008). The expected frequency for each cell in the contingency table was computed as the product of its total row and total column divided by the overall sample size.

The calculated value was then compared with the critical value with (c-1)(r-1) degree of freedom at the 95% confidence level. If the calculated value was greater than the critical value, then the null hypothesis would be rejected. In this study, the Pearson Chi-square test was undertaken using the cross-tab function in SPSS. Table 2 presents the results of Pearson Chi-Square test for the crash attributes listed in Table 1.

Table 2: Results of the Pearson Chi-Square test

Dependent Variable	Explanatory Variables	Significance level (Pearson Chi-Square test)
Crash Severity	Speed zone	<0.0001
	Lighting condition	<0.0001
	Traffic control (other vehicle's approach)	<0.0001
	Traffic control (bicyclist's approach)	<0.0001
	Crash time	<0.0001
	Bicyclist's intent	<0.0001
	Other vehicle's intent	<0.0001
	Road surface (bicyclist's approach)	**0.327**
	Road surface (other vehicle's approach)	**0.331**
	Road geometry	0.042
	Helmet use (bicyclist)	<0.0001
	Location type	0.031
	Bicyclist's gender	0.044
	Bicyclist's age	<0.0001
	Melbourne/greater Melbourne/others	0.007

In the second step, a binary logistic regression model was developed to identify the significant variables as well as the relative importance of the significant variables. The probability of crash i resulting in a fatality or serious injury would be given by:

$$p_i = \frac{EXP(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i})}{1 + EXP(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i})} \quad (2)$$

where β_0 was the model constant

$\beta_1, \ldots, \beta_k$ were the unknown parameters associated with independent variables X_k,

k= 1, ..., K is the set of independent variables

i = 1, …., N is the set of observations.

This model described the relationship between a binary dependent variable and a number of independent variables (Washington et al. 2011). The best estimate of β could be obtained by maximizing the log likelihood function:

$$LL(\beta) = \sum_{i=1}^{n}\{y_i \ln(P_i) + (1-y_i)\ln(1-P_i)\} \tag{3}$$

4. RESULTS

As mentioned above, two-step statistical analysis was carried out in this study. The results of analysis were outlined in the following sub-sections.

4.1. Pearson Chi-Square test

Table 2 illustrates that the majority of independent variables were associated with the dependent variable. As shown in this table the only variables which were not significantly associated with the dependent variable (i.e. crash severity) is road surface for both bicyclist and other vehicle.

4.2. Binary Logistic Regression model

In this study, a binary logistic regression model was developed using the significant variables identified utilizing Pearson Chi-Square test as well as those variables which were not found to be significant using Pearson Chi-Square test but considered as important variables based on theory and evidence from previous studies.

Table 3 shows the results of the binary logistic regression model. In this table, model parameters were estimated for possibility of being involved in a FSI crash compared to a non-FSI crash.

Table 3: Results of the binary logistic regression model

Output Variable	Explanatory Variables	Description/variable levels[a]	Rank (change in log-likelihood ratio)	Significance level (Wald statistic)	Count (Percentage)	Parameters (β)	Odds ratio (exp. β)
The crash is fatal or serious injury crash	Crash Time	0:00 AM to 6:00 AM (ref)	8	-	286 (2.5%)	0	1.00
		9:00 AM to 4:00 PM		0.079	4036 (35.6%)	-0.25	0.77
	Bicyclist's age	Less than or equal to 14 years old (ref)	1	-	996 (8.8%)	0	1.00
		18 to 25 years old		0.02	1632 (14.4%)	0.23	1.26
		26 to 45 years old		0.002	5441 (48.0%)	0.26	1.30
		46 to 65 years old		<0.001	2223 (19.6%)	0.59	1.81
		More than 65 years old		<0.001	367 (3.2%)	0.99	2.70
	Helmet use (bicyclist)	Helmet worn (ref)	6	-	8697 (76.7%)	0	1.00
		Helmet not worn		<0.001	834 (7.4%)	0.47	1.61
	Speed zone	40 km/hr (ref)	3	-	814 (7.2%)	0	1.00
		60 km/hr		0.032	5373 (47.4%)	0.18	1.20
		More than 70 km/hr		<0.001	770 (6.8%)	0.61	1.85
	Lighting condition	Day	7	-	8524 (75.2%)	0	1.00
		Dusk/dawn		0.008	1115 (9.8%)	-0.21	0.81
		Dark		0.014	1542 (13.6%)	0.19	1.21

Output Variable	Explanatory Variables	Description/variable levels[a]	Rank (change in log-likelihood ratio)	Significance level (Wald statistic)	Count (Percentage)	Parameters (β)	Odds ratio (exp. β)
	Other road user's intent	Going straight ahead (ref)	2	-	3881 (34.2%)	0	1.00
		Turning left		<0.001	1695 (14.9%)	-0.52	0.60
		Leaving a driveway		<0.001	664 (5.9%)	-0.47	0.62
		U turning		0.021	167 (1.5%)	-0.43	0.65
		Changing lanes		0.011	207 (1.8%)	-0.42	0.66
		Overtaking		0.094	61 (0.5%)	-0.50	0.60
		Merging		0.001	66 (0.6%)	-1.13	0.32
		Parking or un-parking		0.007	297 (2.6%)	-0.38	0.68
		Stationary (not accident or broke down)		0.007	288 (2.5%)	-0.39	0.68
		Wrong way		0.078	5 (<0.1%)	1.98	7.28
	Traffic control (other vehicle's approach)	No control (ref)	4	-	6818 (60.1%)	0	1.00
		Roundabout		<0.001	963 (8.5%)	-0.51	0.60
		Give way or stop sign		0.003	1383 (12.2%)	-0.21	0.81
		Other		0.056	135 (1.2%)	0.35	1.42
		Unknown		0.021	586 (5.2%)	-0.24	0.79

Output Variable	Explanatory Variables	Description/variable levels[a]	Rank (change in log-likelihood ratio)	Significance level (Wald statistic)	Count (Percentage)	Parameters (β)	Odds ratio (exp. β)
	Bicyclist's intent	Going straight ahead (ref)	5	-	9667 (85.3%)	0	1.00
		Parked legally		0.059	15 (0.1%)	1.02	2.77
		Wrong way		0.013	18 (0.2%)	1.23	3.41
		Not known		<0.001	436 (3.8%)	0.46	1.58
	Constant	-	-	<0.001	-	-0.92	
Model Log Likelihood	Beginning	-7085.482					
	Final model	-6765.599					
Number of observations	11336						

a This column presents significant variable levels

It can be seen in Table 3 that the significant variables were crash time, bicyclist's age and helmet use, speed zone, lighting condition, other road user's intent, bicyclist's intent and traffic control (other road user's approach).

Results of binary logistic regression model revealed that the likelihood of FSI bicycle crashes in dark AM, which is 0:00 to 6:00 AM, is higher than day off peak (9:00 AM to 4:00 PM) with odds ratio of 1.00 and 0.77 respectively. These results are reasonable as higher driving speed and lower visibility could lead to higher severity in bicycle crashes.

The effect of bicyclist's age on bicycle crash severity showed that as the age of bicyclist increased, the possibility of being involved in a FSI crash increased. This association is greater for bicyclists aged more than 45 years old (odds ratios of 1.81and 2.71 for bicyclist's age between 45 and 65 and more than 65 respectively). This finding is consistent with the findings of the study conducted by Boufous et al. (2013).

Bicyclist's helmet use was also a significant variable in the binary logistic regression model. We found that bicyclists who did not use helmet were more involved in fatal and serious injury crashes (with odds ratio of 1.61 compared to odds ratio of 1.00 which is for bicyclists who used helmet). This is a reasonable result as it was expected that using helmets generally reduces the injury severity of bicyclists. This result is consistent with the results of other studies that investigated the effect of bicycle helmet in injury severity reduction (Bampach et al. 2013).

Speed zone was the other significant variable in the model. We found that roads with higher speed limit contributed to more bicycle fatal and serious injury crashes. The possibility of being involved in FSI crashes is substantially higher for speed limit of more than 70 km/hr (with odds ratio of 1.85 compared to 1.20 for roads with 60 km/hr). This result is consistent with the results of the study conducted by Chen and Shen (2016).

Traffic control type for other vehicle's approach was also a significant variable affecting the severity of bicycle crashes. We found that FSI crashes were more likely to take place at intersections in which no control was available compared to = roundabouts (OR=0.60) and stop/give way controls (OR=0.81)

Finally, the intent of bicyclist and the other driver involved in the crash were the other significant variables in the model. We found that "wrong way" was the only vehicle manoeuvre that was associated with high possibility of being involved in FSI crashes compared to "going straight ahead"(OR=7.28) As none of the users involved could expect to see the other, they did not have enough time to perform the appropriate actions. In addition, vehicles which were merging at the time of crash were less likely to be involved in a FSI bicycle crash (odds ratio = 0.32). Regarding the bicyclist's intent, "wrong way" and "parked legally" were the bicyclist's intentions which had highest contribution in FSI crashes (with odds ratio of 3.41 and 2.77 respectively) compared going straight ahead. Therefore, for bicyclist's intent, similar to driver's intent, riding in wrong way had the highest influence on FSI crashes.

As expected, we found that lighting condition also had a significant effect on bicycle crash severity. The results revealed that the probability of being involved in a FSI crash is highest in dark condition (odds ratio = 1.21) and lowest for dusk/dawn condition (odds ratio = 0.81).

The relative importance of the variables in the developed logistic regression model was also indicated. The ranking of the variables was presented in terms of the change in the value of likelihood ratio function (see Equation 3) that was occurred due to the variable. Based on this criterion, bicyclist's age, was ranked as the first variable which had the most effect on the outcome variable. This was followed by other road user's intent, speed zone, traffic control (other vehicle's approach), bicyclist's intent, helmet use (bicyclist) and crash time.

5. SUMMARY AND CONCLUSION

Reducing the severity of bicycle crashes has been the goal of road safety authorities in Australia. Several studies have been conducted in order to find the effect of transport variables on bicycle crash severity. However, very limited studies considered the effect of factors on bicycle FSI crashes in Australia.

This study investigated the effect of crash attributes on bicycle FSI and non-FSI crashes in Victoria, Australia. In this study, two-step analysis has been conducted on the Victorian data base to identify the effect of different variable on bicycle serious casualty crashes in which at least one bicyclist was involved. In the first step, a Chi-Square test was performed to find the significant independent variables. In the second step, a Binary Logistic Regression model was developed to explore the relative importance of the significant variables.

The results of the regression analysis showed that crash time, bicyclist's age and helmet use, speed zone, lighting condition, other road user's intent, bicyclist's intent and traffic control (other road user's approach) were significant. Specifically, the likelihood of bicycle FSI crashes significantly increased in the following conditions:

- Dark AM (0:00 to 6:00 AM) time period
- Bicyclists aged more than 45 years old
- Bicyclists who did not used helmets were involved in more FSI crash
- Speed limit of carriageway was more than 70 km/hr
- Control type is "no control" for other vehicle's approach
- Other road user's intent before crash was driving on wrong way
- Bicyclist's intent before crash was driving on wrong way
- Lighting condition was dark

Results of this study improved the understanding of crash parameters affecting the severity of bicycle crashes. so that relevant countermeasures could be better designed to reduce the number of fatal and serious injury crashes in the Australia road network. It can also help to develop a more reasonable crash typology in order to better identify the problematic crash types and to select more effective countermeasures to tackle bicycle serious injury problems.

Future research should consider more complex methodologies such as ordered probit, ordered logit or mixed logit models to investigate whether better understanding of factors influencing bicycle serious casualty problem could be achieved using these methods.

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