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A random parameter model of factors influencing bicycle fatal and serious injury crashes in Victoria, Australia

Sareh Bahrololoom[1], William Young[2], David Logan[3]

[1] Institute of Transport Studies, Monash University

[2] NanoComm Hub, Department of Civil Engineering, Monash University

[3] Monash University Accident Research Centre, Monash University

Email for correspondence: Sareh.Bahrololoom@monash.edu

Abstract

Bicycle crash statistics revealed that, in 2015, 12 bicyclists died and 107 bicyclists were seriously injured in Victoria. It is necessary to understand the bicyclists' serious casualty problem in order to reduce the number of fatalities and serious injuries in bicycle-involved crashes on the road network. Although a number of studies have investigated the effects of road, environmental, vehicle and human demographic characteristics on number and severity of bicycle crashes, limited research has been conducted to investigate the effects of these parameters on bicycle fatal and serious injury crashes using random parameter modelling technique. Furthermore, there are very few studies conducted in Australia. This study examined the effects of human demographics, road, environmental and crash characteristics on severity of bicycle crashes in Victoria, Australia. Additionally, this study will compare the results obtained from applying random parameter and fixed parameter binary logistic regression modelling techniques. The road crash information system (RCIS) database is used to develop the models. The levels of the dependent variable were 'fatal and serious injury' and 'non-fatal and serious injury'. The results confirmed that the random parameter binary logit model yielded a better result. Further, the results 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 the severity of bicycle crashes.

1. Introduction

Bicyclists' safety on the road network has been a major concern of researchers and authorities in the last decade (Poulos et al. 2015; Sanders 2015). In Australia, in a typical week, about 18% of Australians ride a bicycle for recreation and transport (National Cycling Participation Survey, 2011). Furthermore, between 1991 and 2013, 959 bicyclists died in traffic crashes in Australia (Boufous et al, 2013). In Victoria, in 2015, 12 bicyclists died and 107 bicyclists were seriously injured in traffic crashes. It is important to understand the factors influencing bicyclists' serious casualty problem so we can determine countermeasures that will reduce the number of fatalities and serious injuries in bicycle-involved crashes.

This study examines the effect of road and environment characteristics as well as human and vehicle characteristics on fatal and serious injury bicycle crashes in Victoria, Australia. Additionally, this study will compare the results obtained from applying both random parameter and fixed parameter modelling techniques. Previous road safety studies showed that random parameter models outperformed fixed parameter models. This study will examine this issue.

The next section of this paper outlines previous studies of bicycle safety research. The paper then introduces database used in this study. Then, statistical methods, which were utilized to understand the factors affecting bicycle crash severity, are explained. The data analysis results are outlined next. This is followed by a discussion of results and conclusions.

2. Previous modelling studies

Several studies utilized different modelling techniques to explore the relationship between crash severity and road, environmental, vehicle and human demographic characteristics. Loo and Tsui (2010), Yan et al (2011) and Hu et al. (2014) used binary and multinomial logistic regression models to conduct crash severity analysis on bicycle crashes. Other researchers utilized mixed logit model to understand the factors affecting bicycle crash severity (Moore et al. 2011; Pai 2011; Klassen et al. 2014). Results of these studies showed an improvement in the model goodness of fit since mixed logit account for unobserved heterogeneity in data. Other group of researchers asserted that since crash severity is an ordinal variable, discrete choice modelling techniques with ordinal outcomes should be considered. Klop and Khattak (1999) and Kim et al. (2009) used ordered probit model to analyse the factors affecting bicycle crash severity. There is an assumption in simple ordered logit and ordered probit models which is usually violated. The assumption is that the model parameters are the same for all severity levels. Therefore, researchers suggest that generalized ordered logit, partial proportional odds model and generalized ordered probit are more appropriate modelling techniques (Wang et al. 2015; Chiou et al. 2011; Yasmin et al. 2013). Limited studies utilized generalized ordered probit or logit models to analyse bicycle crash severity (Naveen et al. 2008; Ahsahul Habib and Forbes 2013; Sigal et al. 2013).

In Australia, limited studies were conducted to understand the crash attributes affecting bicycle crash severity (Hutchinson et al. 2008; 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 from 2004 to 2008 were used in this study. Analysis of the police record showed that single bicycle crashes were more likely to happen in the dark, wet conditions and rural areas. Analysis of the hospital data revealed that there was no significant difference between single and multi-vehicles bicycle crashes. While, previous studies had shown that lower levels of crash severity were associated with single bicycle crashes. This might be due to considering both off-road and on-road crash types in previous studies. In the other study, Lawrence et al. (2015) examined the spatial trends in cycling-related injury in Melbourne metropolitan areas. Kernel density estimation and Geographic Information Systems (GIS) were used to find the injury density from 2000 to 2011.

In summary, 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.

To summarise, both random parameter modelling and discrete choice modelling techniques with ordinal outcome were suggested as more reliable methods to understand the factors influencing crash severity. However, the application of these methodologies to understand the factors influencing bicycle serious casualty problem should be examined.

3. Methodology

3.1. Data

Road Crash Information System (RCIS) database was used in this study. It is created using the police report from crash scene. RCIS data includes minor injury, major injury and fatality crashes. There is very limited number of property damage only crashes in this data base.

This database contained useful information about casualty crashes took place in Victoria, Australia. This database included crash attributes such as crash characteristics, vehicle features, collision types and road user characteristics. All two-vehicle casualty crashes, in which at least one bicyclist was involved, were extracted from the RCIS database. The final data set used included bicycle crashes which took place in the Victorian road network between 2004 and 2013. The total number of crashes for the ten years was 11336. Fatal and serious injury (FSI) crashes accounted for 30.7% (3483) of total number of crashes. Table 1 outlines the variables which were used in this study.

3.2. Analysis method

This section explains the statistical methods which were utilized to analyse the data. The dependent variable is 'crash severity' which indicates whether the bicycle crash severity was minor injury fatal and serious injury. In this study, a two-step analysis is carried out to explore the factors associated with a fatal or serious injury bicycle crashes.

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

In the second step, statistical models were developed to understand the relative significance of the factors. The objectives of this study is to understand the factors influencing fatal and serious injury bicycle crashes. Therefore, the dependent variables should be defined as a binary variable indicating whether the crash is a fatal and serious injury crash. Thus, statistical model with binary outcome variables should be utilized.

This study used fixed parameter binary logit and random parameter binary logit models to explore the relative importance of the significant variables. The levels of the dependent variable are 'fatal and serious injury crashes' and 'non fatal and serious injury crashes'.

4. Analysis and results

As mentioned above, a 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

Results of the Pearson chi-square test illustrates that the majority of variables were associated with the dependent variable (at a 90% level of confidence), except road surface for both bicyclist and the other vehicles involved in the crash.

Results of the chi-square test identified the variables which significantly affected bicycle crash severity; however, relative importance of the variables could not be determined using this method. Therefore, it is necessary to run a multivariate modelling technique to achieve this understanding.

Table 1: Variables considered in this study

Variables	Dependent/ independent	Variable levels
Crash severity	Dependent	1:Minor injury; 2: Fatal and serious injury
Other vehicle's intent	Independent	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	Independent	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
Traffic control (other vehicle's approach)	Independent	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)	Independent	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	Independent	If location type was intersection =1, Otherwise =0
Bicyclist's age	Independent	1: <=14; 2: 15-17; 3: 18-25; 4: 26-45; 5: 46-65; 6: >65
Speed zone	Independent	1: 40km/hr; 2: 50km/hr; 3: 60km/hr; 4: >=75km/hr; 5: Other; 6: Not Known
Crash time	Independent	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 layout	Independent	1:Cross intersection; 2:'T' Intersection; 3:Other intersection; 4:Not at intersection; 5:Other
Helmet use (bicyclist)	Independent	1:Crash helmet worn; 2:Crash helmet not worn4; 3:Not appropriate; 4:Not known
Road surface (bicyclist's approach)	Independent	1:Paved; 2:Unpaved; 3:Gravel; 4:Not known
Road surface (other vehicle's approach)	Independent	1:Paved; 2:Unpaved; 3:Gravel; 4:Not known
Lighting condition	Independent	1:Day; 2:Dusk/Dawn; 3:Dark; 4:Unknown
Spatial location	Independent	1:Melbourne; 2:Greater Melbourne; 3:Others
Bicyclist's gender	Independent	1:Male; 2:Female; 3:Unknown

4.2. Binary logistic regression models

Fixed parameter and random parameter binary logistic regression models was developed in this study. Table 2 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.

It can be seen in the Table 2 that the significant attributes were crash time, bicyclist's age, helmet use (bicyclist), 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. This results are reasonable as higher driving speed and low visibility could lead to high severity bicycle crashes in dark AM time.

The effect of bicyclist's age on bicycle crash severity showed that as the age of bicyclist increases the possibility of being involved in a FSI crash is increased. This trend is more severe 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 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. Model parameters showed 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 confirms the results of several studies investigated the effect of bicycle helmet in injury severity reduction (Bambach et al. 2013).

Speed zone was the other significant variable in the model. Model parameters confirms 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 or equal to 70 km/hr (with odds ratio of 1.85 compared to odds ratio of 1.00 and 1.20 for roads with 40 and 60 km/hr respectively). This results confirms the results of the study conducted by Sobhani et al. (2011) and Sobhani et al. (2013).

Traffic control type for other vehicle's approach was also a significant variable affecting the occurrence of bicycle FSI crashes. Estimated model parameters (see Table 3) revealed that FSI crash are more likely to take place at mid-blocks in which no control was available (with odds ratio of 1:00 for both user types in comparison with odds ratio of 0.60 and 0.81 for roundabouts and priority control types respectively). Furthermore, Table 3 showed that roundabouts had the least effect on the likelihood of being involved in a FSI bicycle crash (odds ratio = 0.60).

The intent of bicyclist and the other driver involved in a crash were other significant variables in the binary logistic regression model. Model results illustrated that "wrong way" and "going straight ahead" were the other vehicle's manoeuvres that were associated with high possibility of being involved in a bicycle FSI crash (odds ratio of 7.28 and 1.00 respectively). In can be seen that the possibility of being involved in a FSI crash is significantly higher when the driver was in wrong way (odds ratio = 7.28). This result could be a reasonable consequence as none of the vehicles could expect to see the other one, so they did not have enough time to perform appropriate reaction. 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 comparing to odds ratio of 1.00 for going straight ahead). Therefore, for bicyclist's intent, similar to driver's intent, riding in wrong way had the highest influence on FSI crashes.

Model parameters showed that lighting condition also had a significant effect on bicycle crash severity. The results revealed that the possibility of being involved in a FSI crash is highest in dark condition (odds ratio = 1.21). This possibility is lowest for dusk/dawn condition (odds ratio = 0.81).

Table 2: Results of the binary logistic regression model

Output Variable	Explanatory Variables	Description/variable levels[a]	Significance level	Parameters (β)	Odds ratio (exp. β)
The crash is fatal or serious injury crash	Crash Time	0:00 AM to 6:00 AM (ref)	-	0	1.00
		9:00 AM to 4:00 PM	0.079	-0.25	0.77
	Bicyclist's age	Less than or equal to 14 years old (ref)	-	0	1.00
		18 to 25 years old	0.02	0.23	1.26
		26 to 45 years old	0.002	0.26	1.30
		46 to 65 years old	<0.001	0.59	1.81
		More than 65 years old	<0.001	0.99	2.70
	Helmet use (bicyclist)	Helmet worn (ref)	-	0	1.00
		Helmet not worn	<0.001	0.47	1.61
	Speed zone	40 km/hr (ref)	-	0	1.00
		60 km/hr	0.032	0.18	1.20
		More than or equal to70 km/hr	<0.001	0.61	1.85
	Lighting condition	Day	-	0	1.00
		Dusk/dawn	0.008	-0.21	0.81
		Dark	0.014	0.19	1.21
	Other road user's intent	Going straight ahead (ref)	-	0	1.00
		Turning left	<0.001	-0.52	0.60
		Leaving a driveway	<0.001	-0.47	0.62
		U turning	0.021	-0.43	0.65
		Changing lanes	0.011	-0.42	0.66
		Overtaking	0.094	-0.50	0.60
		Merging	0.001	-1.13	0.32
		Parking or un-parking	0.007	-0.38	0.68
		Stationary (not accident or broke down)	0.007	-0.39	0.68

Output Variable	Explanatory Variables	Description/variable levels[a]	Significance level	Parameters (β)	Odds ratio (exp. β)
		Wrong way	0.078	1.98	7.28
	Traffic control (other vehicle's approach)	No control (ref)	-	0	1.00
		Roundabout	<0.001	-0.51	0.60
		Give way or stop sign	0.003	-0.21	0.81
		Other	0.056	0.35	1.42
		Unknown	0.021	-0.24	0.79
	Bicyclist's intent	Going straight ahead (ref)	-	0	1.00
		Parked legally	0.059	1.02	2.77
		Wrong way	0.013	1.23	3.41
		Not known	<0.001	0.46	1.58
	Constant	-	<0.001	-0.92	0.34
Model Log Likelihood	Beginning -7085.48				
	Final model -6765.60				
Observations 11336					

a This column presents significant variable levels

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 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.

A general concern in the application of binary logit model is the possible random variation in parameters across observations. Such random parameter variations present a serious problem resulting in problematic estimates of parameters and outcome probabilities. To address this problem, random parameter binary logit model has been developed. The literature review of crash severity analysis revealed that random parameter binary logit model can give a better understanding of crash data sets as it allows for relaxation of the independent and identically distributed (IID) condition, addresses the issue of the independence from irrelevant alternatives (IIA) condition, and accounts for unobserved heterogeneity in parameter effects. In order to develop this model, each of the categorical independent variables, which were outlined in the Table 1, was represented by a series of dummy variables. Each category formed a dummy variable which takes 0 and 1 values depending on whether the specific category is present (value = 1) or not (value = 0). The model was run using normal and lognormal distributions. Normal distribution showed the best results.

Table 3 reveals the results of the mixed binary logit model. This table shows that, like the binary logit model, crash time, bicyclist's age, helmet use, speed zone, lighting condition, traffic control (other vehicle's approach), bicyclist's intent and other vehicle's intent were the significant variables in the model.

Morning off peak crash time (9:00 AM to 4:00 PM) was identified as a variable that had random effect on the model outcome as both mean (-0.37) and standard deviation (1.14) were significant. The model parameters showed that in 37% of the times bicycle crashes took place between 9:00 AM and 4:00 PM increased likelihood of being involved in an FSI crash. The possibility of being seriously injured or killed reduced in 63% of the times.

In general, as the age of the bicyclist increased the likelihood of being involved in an FSI crash increased. However, this effect is random for the bicyclists aged more than 65 years old. The results showed that the likelihood of FSI increased in 72% of the occasions.

Table 3 further shows that wearing helmets reduced the likelihood of being involved in a FSI crash. Results also revealed that speed limit of 60 and higher than 70 km/h increased the likelihood of being involved in a FSI crash. This trend was similar to the trend identified using fixed parameter binary logit. Moreover, 'dusk/dawn' lighting condition was found as a significant variable reducing the possibility of FSI crash.

Results of the random parameter model also showed similar trends for the effect of traffic control in other vehicle approach. As shown in Table 3, presence of roundabout reduced the possibility of being involved in a FSI crash.

The general trend for the influence of bicyclist's and other driver's intent was also found to be similar using both random and fixed parameter binary logit models. However, 'going straight ahead' (mean = -0.41, SD = 1.10) and 'turning left' (mean = -2.05, SD = 3.78) were intentions of bicyclist and other vehicle that had random effect on the model outcome respectively. Bicyclist's intent and other driver's intent increased the possibility of being involved in a FSI crash in 35.5% and 29.4% of cases respectively.

Table 3: Results of the mixed binary logit model for factors influencing FSI bicycle crash severity

Dependent variable	Independent variable	Fatal or Serious injury			
		Mean		SD	
		Coefficient	p-value	Coefficient	p-value
Crash severity (reference level = Not Fatal or Serious injury)	Crash time is morning off peak	-0.37	0.020	1.14	0.038
	Bicyclist's age is 18 to 25	0.33	0.049		
	Bicyclist's age is 26 to 45	0.41	0.005		
	Bicyclist's age is 46 to 65	0.85	0.000		
	Bicyclist's age is >65	1.45	0.000	2.45	0.070
	Helmet (bicyclist's) worn	-0.20	0.007		
	Speed zone is 60 km/h	0.25	0.001		
	Speed zone is >= 70km/h	0.97	0.000		
	Lighting condition is dusk/dawn	-0.57	0.039		
	Traffic control for other vehicle's approach is 'no control'	0.27	0.045		
	Traffic control for other vehicle's approach is 'other'	0.84	0.006		
	Traffic control for other vehicle's approach is 'roundabout'	-0.62	0.039		
	Intention of bicycle is 'parked legally'	1.00	0.104		
	Intention of bicycle is 'going straight ahead'	-0.41	0.004	1.10	0.026
	Intention of other vehicle is 'U turning'	-0.38	0.108		
	Intention of other vehicle is 'overtaking'	-0.72	0.074		
	Intention of other vehicle is 'parking or unparking'	-0.34	0.072		
	Intention of other vehicle is 'going straight ahead'	0.15	0.031		
	Intention of other vehicle is 'turning left'	-2.05	0.017	3.78	0.008

	Constant	-0.97	0.002
Model Information	Number of observations = 22672 LR Chi-square = 33.97 (p-value = 0.0012) Log likelihood (0) = -6803.1743 Log likelihood (c) = -6786.1621		

In summary, the results of the binary logit and mixed binary logit showed that although general trends of the significant variables affecting bicycle crash severity were similar and both models were useful to understand the factors influencing bicycle crash severity, mixed binary logit provided extra useful knowledge as it accounts for unobserved heterogeneity in the data.

Results of this model showed that other driver's intent (turning left), bicyclist's intent (going straight ahead), bicyclist's age (>65 years old) and crash time (morning off peak) had random effect on bicycle crash severity.

5. Conclusions

This study investigated the effect of road, environmental, vehicle and human demographic factors on bicycle fatal and serious injury crashes in Victoria, Australia. In this study, a two-step analysis has been conducted on the Victorian data base to identify the effects of different variable on the severity of bicycle crashes. In the first step, a series of chi-square tests were performed to find the significant independent variables. In the second step, both fixed parameter and random parameter binary logistic regression models were developed to explore the relative importance of the significant variables.

In general, both models revealed 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 affected the severity of bicycle crashes. Furthermore, the general trend of the variable effects was similar in both models.

It was concluded that random parameter binary logit provided a better outcome as it allows for relaxation of the independent and identically distributed (IID) condition, addresses the issue of the independence from irrelevant alternatives (IIA) condition, and accounts for unobserved heterogeneity in parameter effects. Results of this model showed that other driver's intent (turning left), bicyclist's intent (going straight ahead), bicyclist's age (>65 years old) and crash time (morning off peak) had random effect on bicycle crash severity. The results further showed that:

- In 37% of the times, bicycle crashes took place between 9:00 AM and 4:00 PM increased likelihood of being involved in an FSI crash. The possibility of being seriously injured or killed reduced in 63% of the times.
- In general, as the age of the bicyclist increased the likelihood of being involved in an FSI crash increased. However, this effect is random for the bicyclists aged more than 65 years old. The results showed that the likelihood of FSI increased in 72% of the occasions.
- Wearing helmets reduced the likelihood of being involved in a FSI crash.
- Speed limit of 60 and higher than 70 km/h increased the likelihood of being involved in a FSI crash.
- Lower possibility of being involved in a FSI crash was associated with Dusk/dawn lighting condition.
- Presence of roundabout reduced the possibility of being involved in a FSI crash.

- Going straight ahead and turning left were intentions of the bicyclist and the other vehicle that had random effect on the model outcome respectively. Bicyclist's intent and other driver's intent increased the possibility of being involved in a FSI crash in 35.5% and 29.4% of cases respectively.

Results of this study improved the understanding of crash parameters affecting bicycle FSI crashes. Some relevant countermeasures could then be designed to reduce the severity of bicycle crashes on Australia roads. It can also help to develop a more reasonable crash typology in order to better identify the problematic crash types. Therefore, more effective countermeasures could be selected to tackle bicycle serious injury problems.

Future studies should consider more detailed analysis of bicycle crash dynamics to better understand the underlying factors influencing bicycle crash severity. Furthermore, other databases such as Transport Accident Commission (TAC) validated crash data should be utilised in future studies to confirm the accuracy of the RCIS data.

References

Ahsahul Habib, M. and Forbes, J.J., (2013). "Modelling bicyclist injury severity levels in the province of Nova Scotia, Canada using a generalized ordered probit model". Transportation Research Board 92nd Annual Meeting, Washington DC, USA

Bambach M.R., Mitchel R.J., Grzebieta R.H and Olivier J. (2013). "The effectiveness of helmets in bicycle collisions with motor vehicles: a case-control study." Accident Analysis and Prevention 53: 78-88.

Boufous, S., et al. (2013). "Single- versus multi-vehicle bicycle road crashes in Victoria, Australia." Injury Prevention 19(5): 358-362.

Chiou, Y.C., et al. (2011). "Modelling two-vehicle crash severity by a bivariate generalized ordered probit approach", 3rd International Conference of Road Safety and Simulation, Indianapolis, USA

Hu, F., et al. (2014). "Related Risk Factors for Injury Severity of E-bike and Bicycle Crashes in Hefei." Traffic Injury Prevention 15(3): 319-323.

Hutchinson, T.P., Kloeden C.N. and Long A.D. (2008). "Overview of pedal cyclist traffic causalities in South Australia." Ergonomics Australia 22(1): 6-15.

Kim, E., et al. (2009). "Factors influencing the severity of bicycle crashes at urban intersections in Korea", ITE Journal 79(8): 23-24.

Klassen, J., et al. (2014). "Analyzing the severity of bicycle-motor vehicle collision using spatial mixed logit models: A city of Edmonton case study." Safety Science 62: 295-304.

Klop, J. R. and A. J. Khattak (1999). "Factors influencing bicycle crash severity on two-lane, undivided roadways in North Carolina." Transportation Research Record (1674): 78-85.

Lawrence, B. M., et al. (2015). "Geospatial Analysis of Cyclist Injury Trends: An Investigation in Melbourne, Australia." Traffic Injury Prevention 16(5): 513-518.

Levine, D.M., Stephan, D.F., Krehbiel, T.C., Berenson, M.L., 2008. Statistics for managers using Microsoft excel Pearson Education, Inc., New Jersey.

Loo, B. and K. Tsui (2010). "Bicycle crash casualties in a highly motorized city." Accid. Anal. Prev. 42(6): 1902-1907.

Moore, D. N., et al. (2011). "Mixed logit analysis of bicyclist injury severity resulting from motor vehicle crashes at intersection and non-intersection locations." Accident Analysis & Prevention 43(3): 621-630.

Naveen, E. et al. (2008). "Mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes". Transportation Research Board 87th Annual Meeting, Washington DC, USA

Pai, C. W. (2011). "Overtaking, rear-end, and door crashes involving bicycles: An empirical investigation." Accid. Anal. Prev. 43(3): 1228-1235.

Poulos, R. G., et al. (2015). "Characteristics, cycling patterns, and crash and injury experiences at baseline of a cohort of transport and recreational cyclists in New South Wales, Australia." Accident Analysis & Prevention 78: 155-164.

Sanders, R. L. (2015). "Perceived traffic risk for cyclists: The impact of near miss and collision experiences." Accident Analysis & Prevention 75: 26-34.

Sigal, K et al. (2013). "Cyclist injury severity in a cycling nation: Evidence from Denmark". Transportation Research Board 92nd Annual Meeting, Washington DC, USA

Sobhani, A., W. Young, and M. Sarvi. A simulation based approach to assess the safety performance of road locations. Transportation research part C: emerging technologies, Vol. 32, 2013, pp. 144-158.

Sobhani, A., W. Young, D. Logan, and S. Bahrololoom. A kinetic energy model of two-vehicle crash injury severity. Accident Analysis & Prevention, Vol. 43, No. 3, 2011, pp. 741-754.

Wang, C., et al. (2015). "Statistical analysis of bicyclists’ injury severity at unsignalized intersections." Traffic Injury Prevention 16(5): 507-512.

Yan, X., et al. (2011). "Motor vehicle–bicycle crashes in Beijing: Irregular maneuvers, crash patterns, and injury severity." Accident Analysis & Prevention 43(5): 1751-1758.

Yasmin, S., et al. (2013). "Analyzing the continnum of fatal crashes: A generalized ordered approach", 2nd Conference of Transport Research Group of India.