Accident Analysis and Prevention 86 (2016) 239–246

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Built environment effects on cyclist injury severity in automobile-involved bicycle crashes

Peng Chen[a,b,*], Qing Shen[a]

[a] Department of Urban Design and Planning, University of Washington, Seattle, USA
[b] Department of Civil and Environmental Engineering, University of Washington, Seattle, USA

ARTICLE INFO

Article history:
Received 17 January 2015
Received in revised form 30 October 2015
Accepted 2 November 2015

Keywords:
Cyclist injury severity
Built environment
Generalized ordered logit model
Generalized additive model
Transportation planning

ABSTRACT

This analysis uses a generalized ordered logit model and a generalized additive model to estimate the effects of built environment factors on cyclist injury severity in automobile-involved bicycle crashes, as well as to accommodate possible spatial dependence among crash locations. The sample is drawn from the Seattle Department of Transportation bicycle collision profiles. This study classifies the cyclist injury types as property damage only, possible injury, evident injury, and severe injury or fatality. Our modeling outcomes show that: (1) injury severity is negatively associated with employment density; (2) severe injury or fatality is negatively associated with land use mixture; (3) lower likelihood of injuries is observed for bicyclists wearing reflective clothing; (4) improving street lighting can decrease the likelihood of cyclist injuries; (5) posted speed limit is positively associated with the probability of evident injury and severe injury or fatality; (6) older cyclists appear to be more vulnerable to severe injury or fatality; and (7) cyclists are more likely to be severely injured when large vehicles are involved in crashes. One implication drawn from this study is that cities should increase land use mixture and development density, optimally lower posted speed limits on streets with both bikes and motor vehicles, and improve street lighting to promote bicycle safety. In addition, cyclists should be encouraged to wear reflective clothing.

1. Introduction

Bicycling provides health, environmental, and social benefits, including decreased rate of obesity, lowered greenhouse gas emissions, reduced congestion, and improved livability. The rise of eco-friendly lifestyles has aided the increasing popularity of cycling activities in the US. However, cyclist injuries remain a serious public health problem. The concern over safety ranks as one of the most important deterrents preventing people from cycling. A recent report shows that only 0.5% of commuters in the US use bicycles as the primary transportation mode (American Association of State Highway and Transportation Officials and US Department of Transportation, 2013). While the number of deaths in traffic crashes kept on declining in the past four decades (The National Highway Traffic Safety Administration, 2012a), the number of reported injured cyclists increased from 45,000 in 2001 to 49,000 in 2012. The percentage of cyclist fatalities among total traffic deaths increased from 1.7% to 2.2% in the same period (The National Highway Traffic Safety Administration, 2012b). Thus, it is important to understand what the leading causes are associated with cyclist injury severity.

Perceived as direct effects correlated with cyclist injury severities, human factors have been widely investigated in prior studies, such as helmet use, intoxication and distraction (Attewell et al., 2001; Cummings et al., 2006; Walker, 2007; Goldenbeld et al., 2012). The exploration of the associations between the built environment and cyclist injury severity is just at the initial stage for two reasons. Firstly, exploring this link requires high quality recorded injury data and knowledge in conducting interdisciplinary research. Secondly, in contrast to driving speed limit, vehicle type and cyclist age, built environment factors are perceived as indirectly associated with cyclist injury severity. Therefore, built environment factors were mostly treated as confounders, or ignored, in prior research.

This paper employs a generalized ordered logit (GOL) model and a generalized additive model (GAM) to identify the main land use and roadway design factors associated with cyclist injury severities for the city of Seattle, Washington. Our research highlights the effects of employment density and land use mixture in mitigating cyclist injury severity.

* Corresponding author. Address: 3949 15th Ave NE, Room 418, Gould Hall, Seattle, WA 98195, United States.
E-mail address: chenp5@uw.edu (P. Chen).

http://dx.doi.org/10.1016/j.aap.2015.11.002

2. Related work

Most bicycle safety studies focus on two issues: bicycle collision frequency and cyclist injury severity. The goal is to find risk factors and offer policy recommendations and roadway design guidelines for safety improvements. Prior studies considered a large set of contributing factors, reclassified as the following categories of variables: (1) demographic profiles, such as age and gender of motorists and cyclists; (2) behavioral factors, such as alcohol and drug use, distraction and inattention, traffic violations and misuse of helmets; (3) vehicle types; (4) roadway design features, such as slopes, bicycle route types, and other characteristics associated with intersections or mid-blocks; (5) traffic controls, such as signals, stop signs and posted driving speed limits; (6) environmental factors, such as the time of day and weather conditions; (7) land use variables, such as density and land use mixture; and (8) crash characteristics, such as the directions and movements of driving and cycling.

Some factors, especially posted driving speed limit, vehicle type, and age of injured cyclists, were regarded as leading causes that generated direct effects on severe crashes (Kim et al., 2007; Walker, 2007; Eluru et al., 2008; Bíl et al., 2010; Chong et al., 2010; Yan et al., 2011). In terms of behavioral factors, the existing safety research ascribed causal effects of the momentary activities of road users on injury outcomes. Furthermore, the effects of protective equipment and improper driving behaviors have been evaluated frequently (Kim et al., 2007; Bíl et al., 2010; Chong et al., 2010; Boufous et al., 2011; Moore et al., 2011). For instance, an empirical study showed that helmet use mitigated the negative effects of cyclist brain injury by more than 85% (Moore et al., 2011).

Environmental conditions were correlated with cyclist injury severity according to prior research. Darkness, measured by the time of day, was a critical factor associated with fatality (Klop and Khattak, 1999; Eluru et al., 2008; Bíl et al., 2010; Boufous et al., 2011). Additionally, adverse environmental conditions, such as wet surfaces, ice and fog, increased the likelihood of serious cyclist injuries (Moore et al., 2011).

In relation to the roadway design factors, prior studies found that signalized intersections with lighting facilities were safer to ride bicycles (Eluru et al., 2008; Bíl et al., 2010; Zahabi et al., 2011). The factors associated with intersection and mid-block injury severity were slightly different (Klassen et al., 2014). Factors affecting the mid-block cyclist injury severity included roadway classifications and on-street parking (Klassen et al., 2014). Zahabi et al. found that cyclist injuries occurred more often but less severe at intersections as compared to those occurring at mid-blocks, which was explained mostly by driving speed reduction at intersection areas (2011). Regarding land use variables, including land use mixture, population density and road connectivity, showed no significant relationships with cyclist injury severity (Zahabi et al., 2011), but the proportions of industrial and commercial land use were positively associated with evident cyclist injuries (Narayanamoorthy et al., 2013).

The ordered categorical attribute of cyclist injury severity has raised some challenging methodological issues (Savolainen et al., 2011; Yasmin and Eluru, 2013; Mannering and Bhat, 2014). Injury severity is typically classified into ordered categories of fatality, severe injury, evident injury (EI), possible injury (PI), and property damage only (PDO). Ordered and unordered response models have been employed to explore how injury severities are correlated with the fixed effects. Yet, injury severity categories are inherently interrelated. Ordered logit model, also known as proportional odds (PO) model, is efficient in capturing the ordinal nature across different levels of injuries (Mooradian et al., 2013). The underlying assumption of a PO model forces the estimated coefficients for covariates to remain constant for all response levels. In other words, the estimated parameters of one factor on all injury types are assumed to be in the same direction. However, some variables may decrease the likelihood of one injury type while increasing the likelihood of another. The effects of some covariates can be reported with bias under the PO modeling framework.

The unordered response models, on the other hand, treat the injury severity as a categorical variable by allowing the factors to influence response levels differently (Yasmin and Eluru, 2013). Additionally, minor bicycle crashes are widely underreported (De Geus et al., 2012, Wegman et al., 2012), especially those occurred on local streets and in rural areas. In this context, the unordered response framework, such as the multinomial logit model or the mixed logit model, is considered to be more effective (Yasmin and Eluru, 2013). The nested logit model is also a type of unordered response model, and it has the advantage of accounting for the ordinal attribute inherent in injury levels within nests. However, some studies found that it did not improve prediction accuracy noticeably to justify the added complexity from the nested structure (Abdel-Aty, 2003; Mooradian et al., 2013).

The partial proportional odds model, short for PPO, offers an appealing option. It relaxes the assumption of an ordinal data attribute and instead assumes that a subset of a fixed covariate affects an injury type independently (Mooradian et al., 2013). An even more flexible modeling framework is provided by the GOL model, which relaxes the constant threshold across injury types, while still accounting for the ordinal nature of the dependent variable (Eluru, 2013; Yasmin and Eluru, 2013).

Another methodological concern is about the spatial dependence among collision sites (Savolainen et al., 2011, Castro et al., 2013). Two types of spatial dependencies, called “spatial spillover” and “spatial correlation,” have been discussed in prior research (Castro et al., 2013). “Spatial spillover” causes the injury risk propensity at one location to influence the likelihood of injury at its neighboring locations. “Spatial correlation” results in locations of the same type sharing similarities in injury risks. The spatial dependence will cause the samples to no longer be independent. Several spatial dependence calculation approaches have been applied to injury severity (Castro et al., 2013; Klassen et al., 2014).

3. Research design

This study uses two models, a GOL model and a GAM to find the built environment factors correlated with different types of cyclist injuries, where cyclist profiles and motorist momentary behaviors are controlled as confounders. The GOL model relaxes the PO model assumption by allowing covariates to affect cyclist injury severities differently. The GAM is employed to further examine these relationships by accommodating possible spatial dependence.

3.1. Model specification

3.1.1. Generalized ordered logit model (GOL)

The GOL model is expressed by Eqs. (1) and (2), which is obtained by assuming that the vector of unobserved utility has a cumulative distribution (Williams, 2006; Agresti and Kateri, 2011; Eluru and Yasmin, 2015). More specifically, supposing an ordinal categorical dependent variable Y_i has M values, the GOL model produces a set of estimates, including $M-1$ cutoff points, at which Y_i can be dichotomized.

$$\ln\left(\frac{P(Y_i > j)}{1 - P(Y_i > j)}\right) = \ln\left(\frac{g(\beta_j X_i)}{1 - g(\beta_j X_i)}\right) = \alpha_j + \beta_j X_i,$$
$$j = 1, 2, \ldots, M-1 \tag{1}$$

$$g(\beta_j X_i) = \frac{\exp(\alpha_j + \beta_j X_i)}{1 + \exp(\alpha_j + \beta_j X_i)} \tag{2}$$