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Statistical Analysis of Bicyclists' Injury Severity at Unsignalized Intersections

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Objectives: This study investigated factors correlated with the severity of injuries sustained by bicyclists in bicycle–motor vehicle crashes at unsignalized intersections to develop site-specific countermeasures and interventions to improve bicycle safety.

Method: Crash data were extracted from accident reports entered into the Kentucky State Police's Kentucky Collision Database in 2002–2012. A partial proportional odds model was developed for data analysis.

Results: According to our modeling results, stop-controlled intersections, one-lane approaches, helmet usage, and lower speed limits were associated with decreased injury severity, whereas uncontrolled intersections, older (age > 55) drivers and bicyclists, child (age < 16) bicyclists, foggy and rainy weather, inadequate use of lights in dark conditions, and wet road surfaces were linked with increased injury severity.

Conclusions: Based on these results, we suggest the development of educational programs focused on the following groups: child bicyclists, older bicyclists, and older drivers. Investigating and modifying street lighting could improve bicycle safety. Implementing road diets/traffic calming methods could create a safer traffic environment. Certain traffic control strategies (e.g., stop control) could be considered for uncontrolled intersections with high bicycle exposure, and helmet campaigns should be launched to increase helmet awareness and use. The study also suggests some interesting future research directions, including examining driver/bicyclist behaviors at uncontrolled intersections and studying the riding behaviors of child bicyclists in Kentucky.

Keywords: injury severity, partial proportional odds model, bicyclists, unsignalized intersections

Introduction

Bicycling is a nonmotorized mode of transport offering health benefits in terms of improving obesity (Hamer and Chida 2008; Lindstrom 2008) and reducing noise and air pollution (Boogaard et al. 2009). Compared to walking, bicycling is faster and up to 5 times more energy efficient (Exploratorium 2014). Hence, bicycling should be encouraged and deserves more attention. In 2010, there were 618 bicyclist deaths and 52,000 bicyclist injuries in the United States. Moreover, the death rate for bicyclists has not shown any downward trend in the past few years (NHTSA 2010). Further, approximately one third of bicyclist deaths occurred at intersections (NHTSA 2010)—usually at unsignalized intersections (Federal Highway Administration 2012). According to Eluru et al. (2008), these intersections are associated with a higher probability of severe bicyclist injuries (+7.48% for incapacitating injuries and +78.25% for fatalities) than signalized intersections. Therefore, to improve bicycle safety, it is important to understand the factors correlated with bicycle injuries and fatalities at unsignalized intersections.

Literature Review

Many studies have contributed to bicycle safety. Some focused on examining factors associated with bicyclists' crash occurrence/frequency. Alcohol was found to significantly increase bicyclists' crash risks (Andersson and Bunketorp 2002; Li and Baker 1994). Age was also found to be a significant factor, in that young (18–24 years) and older bicyclists (>65 years) were more likely to be involved in crashes (Rodgers 1997; Stone and Broughton 2003). Helmet usage was examined as a significant way to prevent bicyclists from being injured (Curnow 2003; Macpherson et al. 2004; Robinson 2001; Schieber and Sacks 2001). As for bike lanes and bicycle crossings, some claimed that these tended to increase the risks of bicycle crashes (Aultman-Hall and Adams 1998; Moritz 1998), whereas others argued that they were more likely to reduce bicyclist injuries (Garder et al. 1998; Pucher 2001). Regarding roundabouts, Schoon and Van Minnen (1994) indicated

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that their implementation was associated with a decrease in both bicyclist crash rates (8%) and injury rates (30%). Hels and Orozova-Bekkevold (2007) found that high traffic volume, higher vehicle speed, and older roundabouts increased the likelihood of bicycle-related crashes.

In addition to these studies, others have extensively studied bicycle–motor vehicle crashes to explore factors associated with bicyclists' injury severity. Klop and Khattak (1999) examined such crashes on 2-lane, undivided roadways using ordered probit models. Darkness, increase in the vertical grade, the presence of horizontal curves along vertical grades, and foggy weather were all associated with higher injury severity. Allen-Munley et al. (2004) modeled 314 bicycle–motor vehicle crashes in Jersey City, New Jersey, using ordinal logistic regression models. Their results indicated that bicyclists were more likely to be severely injured when there was less traffic, wider roads, vertical grades, and one-way traffic. Kim et al. (2007) investigated bicycle–motor vehicle crashes in North Carolina from 1997 to 2002 using a multinomial logit model. Bicyclists older than 55, intoxicated bicyclists, intoxicated drivers, heavy trucks and pickups, traveling at high speeds, driving on curved roads, inclement weather, darkness, and frontal impact were all found to be associated with bicyclists' increased injury severity.

Although substantial effort has been made to examine bicycle safety, few studies have solely examined bicycle–motor vehicle crashes at unsignalized intersections. According to Eluru et al. (2008), these intersections were associated with a higher probability of severe injuries for bicyclists, compared to signalized intersections, indicating the need to separately examine such crashes. Thus, to fill this gap, this study investigates bicycle–motor vehicle crashes at unsignalized intersections in Kentucky. This study aims to explore the factors significantly associated with bicyclists' injury severity and thus provide countermeasures to improve bicycle safety at unsignalized intersections.

Method

Data

According to statistics, bicycle-related crashes in Kentucky increased from 2006 to 2010, and more than half of these were bicycle–motor vehicle crashes (Green et al. 2010).

We extracted data from the Kentucky State Police's Kentucky Collision Database, which contains information gathered from traffic collision reports submitted by law enforcement agencies throughout the Kentucky Commonwealth. The data are based on the observations and judgments of the on-scene state and local police officers (Kentucky Transportation Center and Kentucky State Police 2012). There are 1,715 records in the data from 2002 to 2012. The original data set classifies injury severity into 5 categories: nondetected injury, possible injury, nonincapacitating injury, incapacitating injury, and fatality. From the NHTSA (2000) report on the completeness of crash data, minor injuries are underreported by about 25% throughout the United States, and property-damage-only (PDO) crashes are underreported by at least 50%. Ye and Lord (2011) also pointed out that PDO is the most underreported severity level. The crash database used here has been widely utilized by safety engineers in Kentucky, with full confidence in its completeness and reliability. Thus, in this study, only PDO crashes (i.e., noninjuries) were excluded, and fatal and incapacitating crashes were combined due to the limited number of fatal crashes, resulting in 3 ordered groups per injury severity: slight injury, nonincapacitating injury, and incapacitating injury or fatality (Table 1).

Table 1. Descriptions of injury severity (response variable)

Variables	Description	Number	Percentage
Injury level	Slight injury	710	41.4
	Nonincapacitating	752	43.8
	Incapacitating and fatal	253	14.8

Eighteen factors describing the characteristics of drivers, bicyclists, roadways, and crashes were investigated (Tables 2–4) using a generalized ordered logit model (a partial proportional odds model). Some factors, such as cell phone usage and traffic volume, were excluded due to the lack of this information in the original records.

Most crashes occurred on local streets (69.85%), followed by federal and interstate highways. In Kentucky, local roads account for over 70% of road miles. Though interstate highways and expressways only account for 0.1% of total road miles, they make up around 30% of the vehicle miles traveled. Arterials account for 12.8% of road miles and 38% of the vehicle miles traveled (Highway Performance Monitoring System 2013). Regarding drivers' characteristics, male drivers were involved in 60.82% of the crashes. Young drivers (age < 25) and older drivers (age > 54) accounted for 20.76 and 24.31% of the crashes, respectively, and drivers aged 25 to 54 accounted for 54.93%. A small percentage (10.67%) of drivers were involved in hit-and-run accidents. As for bicyclists, 66.18% were between the ages of 25 and 54. Bicyclists in the <16, 16–24, and over 55 groups accounted for 11.43, 14.58, and 7.81% of the crashes, respectively. Most crashes (80.47%) involved male bicyclists.

Most bicycle–motor vehicle crashes (91.72%) occurred on dry roads, whereas 7.70% occurred on wet ones. Straight and level roads (72.89%) accounted for the largest share.

Table 2. Descriptions of driver and bicyclist characteristics

Categories	Factors	Variables	Number	Frequency (%)
Driver characteristics	Driver gender	Male	1,043	60.8
		Female	672	39.2
	Driver age	<25	356	20.8
		≥55	417	24.3
		25–54	942	54.9
	Hit and run	Hit and stay	1,532	89.3
		Hit and run	183	10.7
Bicyclist characteristics	Bicyclists' age	<16	196	11.4
		16–24	250	14.6
		25–54	1,135	66.2
		55+	134	7.8
	Bicyclists' gender	Female	335	19.5
		Male	1,380	80.5

Table 3. Description of roadway characteristics

Factors	Variables	Number	Frequency (%)
Roadway condition	Icy	12	0.7
	Wet	132	7.7
	Dry	1, 573	91.6
Roadway character	Curve and grade	38	2.2
	Curve and hillcrest	14	0.8
	Curve and level	68	3.9
	Straight and grade	289	16.9
	Straight and hillcrest	56	3.2
	Straight and level	1, 250	72.9
Roadway type	County road	70	4.1
	Federal	214	12.5
	Interstate and state	198	11.6
	Local street	1, 198	69.8
	Other	35	2.0
Traffic control	Stop control	1, 302	75.9
	Yield control	32	1.8
	No control	301	17.6
	Other control	80	4.7
Speed limit	Less than 30 mph	808	47.1
	30 to 40 mph	765	44.6
	40 to 50 mph	100	5.8
	More than 50 mph	42	2.5
Number of approach lanes	Lanes = 1	88	5.1
	Lanes = 2	1, 284	74.9
	Lanes > 2	343	20.0

Stop-controlled and noncontrolled intersections accounted for 75.92 and 17.55% of the crashes, respectively. Speed limits set to less than 30 mph and between 30 and 40 mph accounted for 47.11 and 44.61% of accidents, respectively. Regarding lane number, 2-lane roads accounted for 74.87% of the crashes, followed by roads with 3 or more lanes (20.0%) and one-lane roads (5.31%). Most crashes occurred in the afternoon (45.48%) and evening (30.79%) and at noon (10.38%). Clear days saw 70.72% of the crashes, followed by cloudy days (21.40%) and rainy/foggy days (7.76%). Two major types of crashes were angle crashes (53.70%) and sideswipe crashes (34.34%). Most crashes occurred in daylight (78.13%), whereas 1.87% of the crashes occurred after dark without adequate lighting. Only 6.01% of the bicyclists wore helmets. Of the crashes, 67.23% occurred within urban areas and 32.77% in rural. Passenger cars accounted for 59.3% of the crashes, followed by pickup trucks (13.36%), vans (11.78%), and SUVs (10.96%).

Table 4. Description of crash characteristics

Factors	Variables	Number	Frequency (%)
Collision time	Morning (6 a.m.–11 a.m.)	164	9.6
	Noon (11 a.m.–1 p.m.)	178	10.4
	Afternoon (1 p.m.–5 p.m.)	780	45.4
	Evening (5 p.m.–12 a.m.)	528	30.8
	Night (12 a.m.–6 a.m.)	65	3.8
Weather conditions	Snow/hail	11	0.6
	Clear	1204	70.2
	Cloudy	347	20.2
	Rain/fog	153	8.92
Manner of collision	Angle	921	53.7
	Head on	74	4.3
	Rear end	20	1.2
	Backing	66	3.9
	Sideswipe	589	34.3
	Opposing left turn	45	2.6
Light conditions	Dusk and dawn	125	7.3
	Dark—no lights	74	4.3
	Dark—lights on	504	29.4
	Daylight	1, 012	59.0
Helmets	Helmet usage	103	6.0
	Helmet neglect	1, 612	94.0
Land characteristics	Urban area	1, 153	67.2
	Nonurban area	562	32.8
Vehicle type	Passenger car	1, 017	59.3
	Truck	229	13.4
	SUV	188	10.9
	Van	202	11.8
	Other	79	4.6

The Model

In this study, bicyclists' injury severity is coded on a 3-point scale: 0 = *slight injury*, 1 = *nonincapacitating injury*, and 2 = *incapacitating injury or fatality*. Because injury severity is an ordinal variable, a proportional odds model is more suitable than binary and multinomial models, because these ignore category ordering (Jang et al. 2010). An ordered logit model is a proportional odds model that can be specified as Eq. (1):

$$P(yi > j) = \frac{\exp(X_i' \beta - \mu_j)}{1 + \exp(X_i' \beta - \mu_j)}, \; j = 1, 2, \ldots, M - 1, \tag{1}$$

where j is a category of injury severity, X_i is a vector of explanatory variables, β is a vector of parameters of explanatory variables that need to be estimated, μ_j are threshold cut points of the ordered logit model, and M is the number of response variable categories.

An important assumption in proportional odds models is the parallel lines assumption that variables are assumed to have constant effects (i.e., constant coefficients) across different levels; however, this assumption is often violated because some variables have changing effects (i.e., different coefficients) between different levels. If this assumption is violated by some explanatory variables, the proportional odds models (e.g., ordered logit and probit models) could result in incorrect, incomplete, or even misleading results (Kaplan and Prato 2012). In this case, a partial proportional odds model will adequately address this issue, because it is less restrictive in that it does not require all variables to follow the parallel lines assumption and is more parsimonious than binary and multinomial logit/probit models (Williams 2006). For a partial proportional odds model (e.g., a generalized ordered logit model), the probability of injury for a given crash can be specified as Eq. (2):

$$P(yi > j) = \frac{\exp(X_{1i}\,\beta_1 + X_{2i}\,\beta_{2j} - \mu_j)}{1 + \exp(X_{1i}\,\beta_1 + X_{2i}\,\beta_{2j} - \mu_j)}, \quad j = 1, 2, \ldots, M - 1, \tag{2}$$

where β_1 is a vector of parameters that does not violate the parallel lines assumption and is associated with a subset of explanatory variables (X_{li}) and β_{2j} is a vector of parameters that vary according to the cut point of the proportional odds model and is associated with a subset of other explanatory variables (X_{2i}).

The marginal effect of a variable represents how this factor affects the response variable on the underlying scale. For continuous variables, the derivative is calculated numerically. However, for dummy variables, a difference is calculated instead of the derivative. The pseudo R^2 measure and Akaike's information criterion (AIC) are used to measure the model fit (Train 2003).

Results

Two partial proportional odds models with logit and probit functions were developed and compared according to their AIC. The partial proportional odds model with logit functions is reported in this article because it performed better with a smaller AIC (AIC = 3,628.195 vs. 3,637.324). The parallel lines assumption for each variable was tested using a series of Wald tests. Only one variable violated the assumption: driver age > 55. This variable displayed different coefficients (effects) between different levels of injury severity, whereas the other variables maintained constant coefficients (effects) across all severity levels. The nature of partial proportional odds models makes it possible to explain these effects. Table 5 shows the modeling results. Table 6 shows the significant factors' marginal effects.

Both older bicyclists (over 55; $P = .000$, $\alpha = .129$) and child bicyclists (under 16; $P = .009$, $\alpha = .241$) were more likely to be severely injured. The marginal effects show that older bicyclists are more likely to be involved in nonincapacitating (+3.9%) and incapacitating or fatal crashes (+1.9%). This could be due to their reduced physical abilities (in reacting to and avoiding crashes) and greater fragility compared to other age groups (Eluru et al. 2008).

Table 5. Partial proportional odds model for bicyclist injury severity[a]

	Variables	Coefficient	SD	P value	95% Confidence interval Lower	Upper
Threshold between 0 and 1	Stop control	−0.435	0.173	<.001	−0.774	−0.096
	No control	0.376	0.204	<.001	−0.024	0.776
	One-lane approaches	−0.702	0.253	<.001	−1.198	−0.206
	Speed limit < 30 mph	−0.779	0.224	<.001	−1.218	−0.340
	Dark—no lights	0.901	0.487	<.001	−0.054	1.856
	Wet	0.225	0.162	<.001	−0.093	0.543
	Rain/fog	0.617	0.243	<.001	0.141	1.093
	Helmets	−1.113	0.155	<.001	−1.417	−0.809
	Bicyclist age < 16	0.416	0.077	.009	0.265	0.567
	Bicyclist age > 55	0.189	0.093	<.001	0.007	0.371
	Truck	0.642	0.183	<.001	0.283	1.001
	Van	0.833	0.190	<.001	0.461	1.205
	Driver age > 55	0.242	0.092	.013	0.062	0.422
Thresholds 1 and 2	Driver age > 55	0.979	0.091	<.001	0.621	0.977
	ω_1	1.287	1.108	<.001	−0.885	3.459
	ω_2	2.701	1.216	<.001	0.318	5.084
	Log likelihood	−1,798 .097				
	Pseudo R^2	0.152				

[a]0 = slight injury, 1 = nonincapacitating injury, 2 = incapacitating injury and fatality.

Table 6. Marginal effects of significant variables in the partial proportional odds model

Variables	Slight	Nonincapacitating	Incapacitating and fatal
Stop control	0.111	−0.081	−0.042
No control	−0.097	0.064	0.032
One-lane approaches	0.199	−0.162	−0.074
Speed limit < 30 mph	0.205	−0.174	−0.081
Dark—no lights	−0.281	0.193	0.112
Wet	−0.060	0.031	0.015
Rain/fog	−0.125	0.097	0.052
Helmets	0.311	−0.229	−0.125
Bicyclist age < 16	−0.105	0.082	0.039
Bicyclist age > 55	−0.043	0.039	0.019
Truck	−0.148	0.125	0.063
Van	−0.218	0.184	0.093
Driver age > 55	−0.049	0.059	0.061

The marginal effects further show that child bicyclists are more likely to be involved in both nonincapacitating (+8.2%) and incapacitating or fatal crashes (+3.9%). This is consistent with Doong and Lai's (2012) results that child bicyclists were more likely to be severely injured at locations without traffic signals. A recent survey carried out by BoltBurdonKemp (2014) showed that 40% of bicyclists younger than 16 in London used cell phones while cycling, without regarding the danger. Moreover, 30% of these bicyclists never received advice or formal education on cycling safety. Fraser et al. (2012) suggested that factors including lack of strength to negotiate hazards, limited speed and distance perception, limited traffic experience and knowledge, and risk-taking behaviors might affect child bicyclists' safety and require more attention. However, current crash data do not reveal information on their riding behaviors or their risk factors at Kentucky's unsignalized intersections. Furthermore, no studies have considered this issue.

Drivers over 55 violate the parallel lines assumption. According to Table 5, these drivers are more often involved in more severe injury crashes involving bicyclists. Regarding marginal effects (Table 6), they are correlated with increased risks of nonincapacitating injuries (+5.9%) and incapacitating or fatal (+6.1%) injuries. This could be because older drivers normally have delayed perception and relatively slow reaction times in taking evasive actions (Eby et al. 1998), resulting in a higher precrash speed that increases the force of impact. However, they are correlated with decreased risks of slightly injured (−4.9%). One reason could be that older drivers tend to be less aggressive than other drivers. Shinar and Compton (2004) found that drivers over age 45 are less likely to drive aggressively than younger drivers. Similar results have been found by Vanlaar et al. (2008).

Bicyclists were more likely to be severely injured in rainy and foggy ($P = .000$, $\alpha = .617$) weather. Furthermore, they were at greater risk of being involved in nonincapacitating (+9.7%) and incapacitating or fatal (+5.2%) crashes. As Kim et al. (2007) stated, rainy and foggy weather lowers visibility for bicyclists and drivers, which could result in a shorter reaction distance and higher closing speed. According to Klop and Khattak (1999), fog is correlated with bicyclists' increased injury severity.

Wet roads ($P = .000$, $\alpha = .225$) are positively correlated with bicyclists' injury severity levels. Additionally, wet roads are associated with increased chances of nonincapacitating (+3.1%) and incapacitating or fatal (+1.5%) crashes. Understandably, drivers and bicyclists would more likely lose control on wet roads than on dry roads.

Dark without lights ($P = .000$, $\alpha = .901$) was found to be associated with increased risks of nonincapacitating injuries (+19.3%) and incapacitating injuries and fatalities (+11.1%). As Habib and Forbes (2014) stated, poor lighting conditions could aggravate bicyclists' injury severity by reducing visibility, resulting in lack of evasive actions and increased precrash speeds. Notably, to thoroughly examine the effects of lighting, bicycle illumination equipment should also be an important concern. It is unknown from the current data how many of the bicycles involved in the crashes had such equipment.

Bicyclists were less likely to be severely injured at unsignalized intersections that have low speed limits (<30 mph; $P = .000$, $\alpha = -.779$). Table 6 shows that these speed limits are associated with decreased probability of nonincapacitating injuries (−17.4%) and incapacitating injuries and fatalities (−8.1%). According to Eluru et al. (2008), speed limits often serve as a surrogate measure of actual vehicle speed at the point of impact, indicating the strong relationship between the two. These results show that low speed limits could be related to low precrash vehicle speeds, which decrease the force of impact and reduce bicyclists' injury severity. This could also reflect the finding that roadways with low speed limits normally have low traffic volumes.

One-lane ($P = .001$, $\alpha = -.702$) approaches were negatively correlated with bicyclists' injury severity. According to Table 6, they are significantly related to decreased probability of nonincapacitating (−16.2%) and incapacitating or (−7.4%) fatal injuries of bicyclists. From a design perspective, intersections with fewer lanes have less conflict points between bicycles and motor vehicles. Moreover, these roads are normally designed for lower traffic volumes and therefore have less traffic exposure. Thus, one-lane approaches are relatively less dangerous to bicyclists. Additionally, drivers and bicyclists both may tend to drive more cautiously due to the limited road space.

Severe bicyclist injuries are less likely to occur at stop-controlled intersections ($P = .000$, $\alpha = -.435$), which are associated with increased risk of nonincapacitating (−8.1%) and incapacitating or fatal (−4.2%) crashes. By contrast, bicyclists are more likely to be severely injured at uncontrolled intersections ($P = .000$, $\alpha = .376$), which are correlated with increased chances of nonincapacitating (+6.4%) and incapacitating or fatal (+3.2%) injuries. Drivers normally decelerate before reaching stop-controlled intersections, which reduces their speeds near intersections. However, the data do not clearly reveal either drivers'/bicyclists' behaviors at uncontrolled intersections or whether these behaviors differ significantly from those at other locations (e.g., stop-controlled intersections). Notably, no obvious trend exists indicating that the speed limit at uncontrolled intersections is higher than at other intersections. Thus, motorists' behaviors at uncontrolled intersections require further examination.

Consistent with previous studies, bicyclists wearing helmets are less likely to be severely injured ($P = .000$, $\alpha = -1.113$; Curnow 2003; Macpherson et al. 2004; Robinson 2001; Schieber and Sacks 2001). Notably, Kentucky has no bicycle helmet law (NHTSA 2008), and 93.99% of bicyclists who crashed were not wearing helmets (no statewide estimate of helmet use exists). Thus, enacting a bicycle helmet use law may improve bicycle safety. Helmet laws were found to significantly reduce bicycle usage (Clarke 2012); thus, helmet campaigns should be considered as a viable alternative.

As expected, vans ($P = .000$, $\alpha = .833$) and pickup trucks ($P = .000$, $\alpha = .642$) are more likely to be involved in severe bicycle–motor vehicle crashes. As Kim et al. (2007) pointed out, heavier vehicles have greater momentum at a certain speed than do passenger cars, thus increasing the probability of more severely injuring cyclists. Other likely factors include line-of-sight and decreased maneuverability. Given the current crash data, however, it is not possible to investigate these effects.

Discussion and Conclusions

This study investigated bicycle–motor vehicle crashes at unsignalized Kentucky intersections using a generalized ordered logit model. Importantly, we found that (1) child bicyclists are more likely to be severely injured at unsignalized intersections and (2) uncontrolled intersections are correlated with more severe cyclist injuries, whereas stop-controlled intersections are related to less severe injuries. Additionally, older drivers and bicyclists (age > 55) were more likely to be involved in severe crashes but less likely to be involved in minor-injury crashes. Bicyclists are more likely to be severely injured on wet roads, under adverse weather conditions, and in dark areas, whereas they are less likely to be severely injured at unsignalized intersections with fewer motorized lanes. Large vehicles, including pickup trucks and vans, are more likely to be involved in severe crashes. Helmet usage is linked to the decreased probability of bicyclists' severe injuries.

Based on these findings, we suggest the following safety interventions and countermeasures. Drivers and bicyclists, especially children, need to be better educated in terms of personal safety awareness when crossing unsignalized intersections. Investigating street lighting at unsignalized intersections could possibly increase bicycle safety. We found that fewer motorized lanes and lower speed limits are linked to bicyclists' decreased injury severity. This result supports the implementation of road diets and traffic calming measures to create a safer nonmotorist traffic environment. Uncontrolled intersections with high bicycle exposure need to be examined in terms of possible conversion to stop-controlled intersections. Helmet campaigns should also be expanded to encourage use. Moreover, these results present some interesting directions for future research examinations, such as driver/bicyclist behaviors at uncontrolled intersections, riding behaviors of child bicyclists at unsignalized intersections, and potential factors related to the more severe bicycle accidents caused by heavy trucks.

This article suffers from the following limitations: (1) Factors such as cell phone usage and traffic volume could not be analyzed due to lack of information and (2) minor injury crashes are often underreported, leading to inaccurate model estimates. Nevertheless, these findings provide useful information for traffic safety engineers to better understand the implications for cyclists at unsignalized intersections in Kentucky.

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