An Assessment of Traffic Safety Between Drivers and Bicyclists Based on Roadway Cross-Section Designs and Countermeasures Using Simulation

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UNIVERSITY TRANSPORTATION CENTER

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Abstract

Cycling is encouraged in countries around the world as an economical, energy-efficient, and sustainable mode of transportation. Simulation is an important approach to analyzing the safety of cycling by identifying the effects of different factors. To ensure the success of a simulation study, it is essential to know the factors that have significant effects on bicycle safety. Although many studies have focused on analyzing bicycle safety, they lack bicycle exposure data, which could introduce biases for the identified factors. This study represents a major step forward in estimating safety performance functions for bicycle crashes at intersections by using crowdsourced data from STRAVA. Several adjustments considering the population distribution and field observations were made to overcome the disproportionate representation of the STRAVA data. The adjusted STRAVA data that includes bicycle exposure information was used as input to develop safety performance functions. The functions are negative binomial models aimed at predicting frequencies of bicycle crashes at intersections.

The developed model was compared with three counterparts: a model using the un-adjusted STRAVA data, a model using the STRAVA data with field observation data adjustments only, and a model using the STRAVA data with adjusted population. The results revealed that the STRAVA data with both population and field observation data adjustments had the best performance in bicycle crash modeling.

The results also addressed several key factors (e.g., signal control system, intersection size, bike lanes) that are associated with bicycle safety at intersections. It is recommended that the effects of these identified factors be explored in simulation studies. Additionally, the safety-in-numbers effect was acknowledged when bicycle crash rates decreased as bicycle activities increased. The study concluded that crowdsourced data is a reliable source for exploring bicycle safety after appropriate adjustments.

1 Introduction

1.1 Bicycle Safety

The transportation-related challenges of traffic congestion and road-safety concerns are the main problems facing transportation agencies worldwide. Recently, sustainable modes of transportation have been encouraged by governmental agencies in order to increase green cities and counteract global climate changes. Countries around the world are increasingly turning to promoting bicycling as an economical and energy-efficient form of transportation. Bicycling could have many potential benefits, such as reducing air pollution, congestion, and fuel consumption, in addition to promoting public health and decreasing stress levels [1-3]. Recently, bicycle usage in the U.S. has increased markedly and is considered one of the main active transportation systems that promote the effective use of road space and parking, in addition to offering energy-efficiency benefits. Nevertheless, cyclist safety is recognized as a serious problem in the U.S.; between 2004 and 2013, bicyclist fatalities increased from 1.7% to 2.3% [4]. This risk is one of the main things that discourage people from choosing cycling as a major travel mode. Hence, improving the bicycle infrastructure and evaluating bicycle safety have become increasingly crucial.

Previous studies have found that intersections are one of the hotspots for the occurrence of bicycle crashes [5-11]. Nordback et al. [12] developed bicyclist-safety performance functions at the intersections of Boulder, Colorado. The authors discovered a non-linear relationship between bicycle trip frequencies and bicycle-motorist crashes. Similarly, there was also a non-linear relationship between vehicle volume and bicycle-motorist crashes. The results also showed that bicycle crash rates decreased at intersections with more bicycle volume (the concept of safety in numbers) [12]. Abdel-Aty et al. [7] carried out a study to explore the contributing factors affecting bicycle crash frequencies. The authors developed four negative binomial (NB) models. The results reported that bicycle safety is associated with the presence of intersections and areas where the speed limit is 35 mph [7]. Siddiqui et al. [8] developed Bayesian Poisson-lognormal models accounting for spatial correlation of bicycle crashes. The results showed that several factors significantly increase bicycle crashes, including intersections, population density, and urban areas [8]. Cai et al. [5] found that several factors have a significant impact on bicycle crashes using a zero-inflated negative binomial spatial model. These factors include signalized intersections, population density, employment count, vehicle miles traveled (VMT), sidewalk length, local roads' length, and number of pedestrians and cyclists [5].

In bicycle safety analysis studies, exposure could be bicycle volume [13], traffic volume [14], bicycle trip distance [15], bicycle trip time [16], population [17], or risk of injury [18]. Vanparis et al. [19] concluded that bicycle exposure should be included in bicycle safety analysis. On the contrary, they reported that there is a lack of good bicycle exposure measures. Strauss et al. [20] performed a study for analyzing bicycle injury crashes at 647 intersections using the Bayesian modeling approach. The bicycle flow from the Montreal Department of Transportation was used as the exposure. The study found that there is a significant association between bicycle volume and injury crash count occurring at intersections. Specifically, injury crashes increased by 0.87%

for every increase of 1% of bicycle volume. Another study by Strauss et al. [21] used smartphones' GPS tracers in order to collect bicycle trip data at intersections. The results of the study uncovered that a bicycle facility (e.g., cycle track, bicycle path) had a significant effect in increasing bicycle count at signalized intersections. In addition, cycle tracks have a positive impact on reducing cyclist risk. The study emphasized the importance of using GPS in collecting data since it generates a large amount of spatial bicycle data.

1.2 Crowdsourced data

To date, there are limited sources of bicycle data for estimating bicycle traffic volumes. Recent studies utilized some data sources for analyzing bicycle trips and safety. Generally, bicycle volumes can be collected from crowdsourced GPS tracers [22-24], automated counters, observed data for links or intersections, or travel surveys [25]. Due to the high cost and limitations of the observed data, crowdsourced GPS tracers are the preferred data source due to their low cost and the availability of cyclist characteristics compared to other available sources. Crowdsourced GPS applications, such as STRAVA and MapMyRide, are considered Big Data sources. Researchers refer to these applications as Big Apps [22].

Jestico et al. [23] conducted a study to predict cyclist volumes using STRAVA crowdsourced data by tracking routes using GPS. Categorical breakdowns were used for predicting the cyclist volumes. Generalized linear models with Poisson distribution were conducted, and the results showed that the spring and summer months had the highest cycling volume when compared to other time periods. The presence of bike facilities (i.e., painted bike lanes and paved multi-use trails) did not appear to affect the cycling volume prediction. The findings of the study revealed that crowdsourced data from STRAVA had a linear correlation with field count data. However, STRAVA users represent a sample of the overall actual number of cyclists. The authors also concluded that STRAVA data is a good indicator of the actual bicycle volume [23].

Another study was conducted by Hochmair et al. [24] to identify the factors that affect the cyclist volume from STRAVA data. Linear regression models were developed for predicting the bicycle kilometers traveled (BKT). The results of the study revealed that bicycle volume was found to have a positive correlation with the presence of recreational trails for cyclists and pedestrians. Additionally, BKT increased at roads that have low-speed traffic, such as locals and collectors, when compared to other types of roads. The results confirmed that use of STRAVA data can be considered an appropriate approach for estimating cyclist volume. However, it was skewed towards young, male cyclists [24]. A study conducted by Sun et al. [26] utilized STRAVA data for evaluating air pollution exposure. The study utilized the crowdsourced data to investigate the relationship between active travel and active pollution concentration as a further step for potential policy-making [26]. Heesch et al. [27] used STRAVA data for evaluating the impact of bicycle infrastructure on cycling behavior. In general, few studies used STRAVA crowdsourced data as a source of bicycle data, whereas there was no study conducted to overcome the disproportionate representation of the data [27].

1.3 Geometric Design and Built-In Environment Characteristic

Different geometric design characteristics were used in this study, including bike lane, bike lane width, sidewalk, sidewalk width, median, median width, and raised median. From previous studies, these seemed to be the characteristics best suited to helping improve bicycle safety at intersections. According to Sadek et al. [28], based on survey data, the installation of an advanced bike lane helps increase awareness of drivers and bicyclists. The responses showed that 75.4% of drivers believed that the new bike lane made drivers more aware of the presence of bicyclists. The survey also showed that 76% of bicyclists said that the new bike lane had made them more vigilant. The results showed that adding a bike lane on urban arterials has positive safety effects (i.e., CMF < 1) for all crashes and for bike crashes [29]. It was found that adding a bike lane is more effective in reducing bike crashes than all crashes.

The presence of a raised median, on the other hand, is expected to reduce crashes. According to Strauss et al. [20], the presence of a raised median at an intersection reduces injury occurrence by over 42%. Raised medians are found along at least one approach in many of the intersections in this study. Medians place constraints on motor-vehicle movements and can provide a refuge for cyclists who may have run out of time to safely cross the intersection. It is also important to mention that the presence of bicycle lanes at intersections was also tested. Only a small number of intersections in this study have bicycle facilities in the intersection. This may explain why they were not found to be significant. Therefore, there is not enough evidence to establish a positive (or negative) association between bicycle facility presence and injury frequency at signalized intersections. The presence of bicycle facilities at intersections was not found to be statistically associated with injury frequency, but it has been found to increase cyclist volumes [20]. Not surprisingly, intersections with bicycle facilities have a significantly higher concentration of cyclists. This means that, after controlling for other factors, intersections with bicycle facilities, with higher cyclist volumes, are expected to witness greater injury frequency but lower injury rates.

To clarify the relationship between cycling and the built environment, methodological refinements tailored to cycling are needed. Factors such as the local availability of sidewalks or land use mix may be primary motivators of walking trips, but decisions on whether to cycle may be influenced by a different suite of factors across spatial areas beyond the trip origin [30]. According to Winters et al. [30], in a survey querying 73 factors, the top four motivators for making a trip by bicycle were related to routes: being away from traffic and noise pollution, having beautiful scenery, having separated bicycle paths for the entire distance, and having flat topography. The geographic accessibility of destinations (i.e., schools, employment sites, retail) may also affect the likelihood of making trips by bicycle, and since two-thirds of cycling trips are under 5 km and 90% are less than 10 km, short trip distances are important.

According to Strauss et al. [20], intersections with three approaches are expected to have fewer cyclists than intersections with four approaches (with an elasticity of 0.77). This factor can be seen as a proxy for intersection connectivity. Strauss et al. [20] also noted that, not surprisingly, the presence of bicycle facilities near an intersection has an important effect on bicycle activity. Intersections near bicycle facilities have a much higher concentration of bicycle flows with an elasticity of 0.288 and C.I. [0.131, 0.146].

Using a novel methodology tailored to cycling, Winters et al. [30] found that the built environment influenced decisions to bicycle instead of drive after accounting for trip distance and personal demographics. This study characterized the built environment around the trip origin and destination and along the route between the two, and found increased bicycling with less hilliness; fewer arterial roads and highways; higher intersection density; presence of bicycle-specific infrastructure including traffic calming, signage, road markings, and cyclit-activated traffic lights; more neighborhood commercial, educational, and industrial land use; less large commercial and single-family housing land use; greater land use mix; and higher population density.

Changes in the built environment are expected to cause direct changes in bicycle volumes and therefore indirect changes in injury frequency and injury risk at intersections. For instance, after the installation of a new bicycle facility crossing an intersection, bicycle flows are expected to grow, as will the number of injuries without appropriate countermeasures [20].

1.4 Bicycle Safety Countermeasure

Countermeasures that can be used to help reduce bicycle-motor vehicle (BMV) crashes would be bike lanes (preferably bike lanes in between through and turn lanes), sidewalks, and medians (preferably raised medians). Other typical countermeasures include the reduction of turning radii, the implementation of an exclusive bicycle and pedestrian signal phase, bike boxes, etc. According to Strauss et al. [20], restricting turning vehicular movements is a common practice in cities like Montreal; however, it may simply move the problem to neighboring intersections and can have negative impacts on network connectivity, travel times, and delays. This countermeasure may, however, be justifiable at intersections with very high cyclist flows.

When it comes to bicycle safety for roadway segments, the best countermeasures to use are bike lanes, bike paths, medians, and raised medians. These countermeasures will help decrease the risk of BMV crashes in the roadway segments.

When it comes to studies on bicycle safety in the US, there are not that many. Cyclist safety studies at intersections are rare in North America; most have been carried out in European and Asian cities [12]. While a few studies have been carried out in the United States and Canada, these have mainly focused on cyclist injuries at the bicycle facility, city, or town level and did not focus on intersections (junctions) as the unit of study [31]. Oh et al. [32] revealed that bicycle crashes at urban intersections in Inchon, Korea, increase with increasing average daily traffic volume, with number of driveways, and in the presence of crosswalks and industrial land use. Crashes were found to decrease with increasing sidewalk widths and in the presence of bus stops and traffic-calming measures. For non-signalized intersections, some countermeasures can be adopted for safety. Stop signs, which are typical for most intersections in North American neighborhoods, can be removed in the direction of the bicycle travel along these routes to facilitate continuous travel without dismounting at every intersection [33]. These are just some of the countermeasures that could be adopted when it comes to bicycle safety. It is expected that, in the future with the use of current and future research, other countermeasures could be developed to help increase bicycle safety.

1.5 Study Objectives

As discussed above, previous studies have shown that bicyclists are more likely to be involved crashes at intersections [5-11]. A lot of factors have been revealed in the previous studies. It was also concluded that there is a lack of good exposure for bicycle crash modeling, which may introduce biases for the effects of identified factors. Moreover, smartphone GPS data (i.e., STRAVA data) has been utilized in limited studies as a reliable source of bicycle exposure for bicycle safety analysis [21, 34, 35]. STRAVA can generate a significant amount of bicycle data tracked by GPS. However, the data needs some adjustments since it is skewed towards young male cyclists and represents a sample of the actual bicycle data [23, 24, 34, 35].

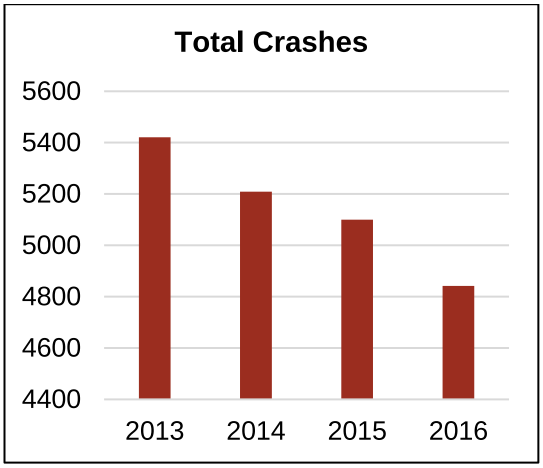
This work draws on the strengths of the crowdsourced data for analyzing bicycle safety. Negative binomial models are used for developing safety performance functions (SPFs) for bicycle crashes occurring at intersections. Several adjustments were applied to the STRAVA data to overcome the disproportionate representation and the spatial biases of the crowdsourced data. The optimal STRAVA data adjustment was determined based on the model performance. This paper is composed of five sections. Following this section, the second section provides a review of the data preparation. Section 3 describes the STRAVA data manipulation, which mainly included population representation and field adjustments. The fourth section provides the results of the bicycle safety performance functions. The last section summarizes the conclusions and discusses the implication of the findings for future research.

2 Data Preparation

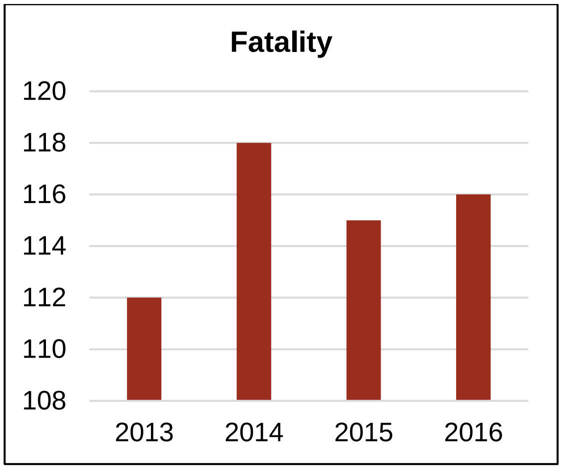
Now that the bicycle-safety-related studies have been presented in the literature review, we will discuss the specific data to be used in the study. Data from the intersections of Orange County, Florida, were used for the analysis. Orange County was selected due to the relatively high rate of bicycle commuting in Florida, as well as high rates of bicycle crashes. Intersections are the focus since the majority of bicycle crashes are found to occur there. Various types of datasets were used for analyzing bicycle safety at intersections. These datasets are as follows: bicycle crash data, bicycle volume from STRAVA data, and road geometry data.

2.1 Bicycle Crash Data

Bicycle crashes were collected from Florida Signal Four Analytics (S4A) over the course of four years (2013-2016). Three different crash severities were defined in the dataset: fatality, injury, and property damage only (PDO). Crashes involving bicycles represented 0.79% and 4.5% of total crashes and fatal crashes, respectively. Figure 2.1 shows the crash frequency for each severity level. Total bicycle crashes were reduced by 10.6% from 2013 to 2016. Injury and PDO crashes followed the same trend, whereas fatality bicycle crashes fluctuated over the years. In Florida, between 2013 and 2016, 55% of all bicycle crashes and 38% of fatality crashes were at intersections, possibly because bicycles have more interaction with vehicles at intersections.



(a)



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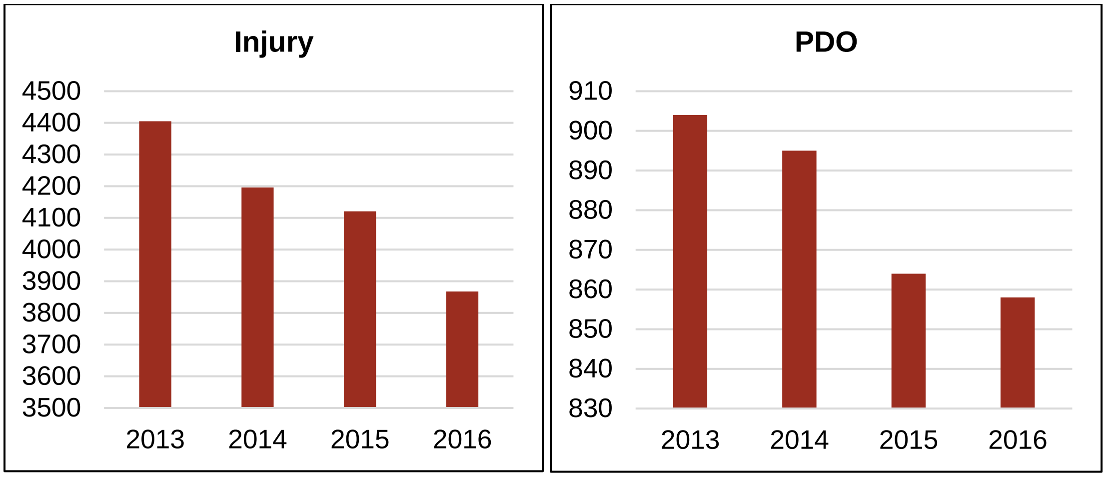

(c) (d)

Figure 2.1 - Bicycle crashes in Florida

In Orange County, 976 bicycle crashes were observed near intersections from 2013 to 2016. Orange County has the third-highest rate of bicycle crashes among all counties in Florida (9%) after Miami-Dade County (9.5%) and Broward County (11%), as shown in Figure 2.2. Additionally, the highest number of fatal bicycle crashes occurred in the intersections of Orange County, contributing 10.7% overall. The majority of bicycle crashes in Orange County occurred at intersections, with 54% compared to other sections. Figure 2.3 shows the bicycle crash distribution in Orange County. For the three-legged intersections, the percentages of the three severity levels were as follows: 13% PDO, 85% injury crashes, and 2% fatal crashes. For the four-legged intersections, the percentages of the three severity levels were as follows: 16% PDO, 82% injury crashes, and 2% fatal crashes.

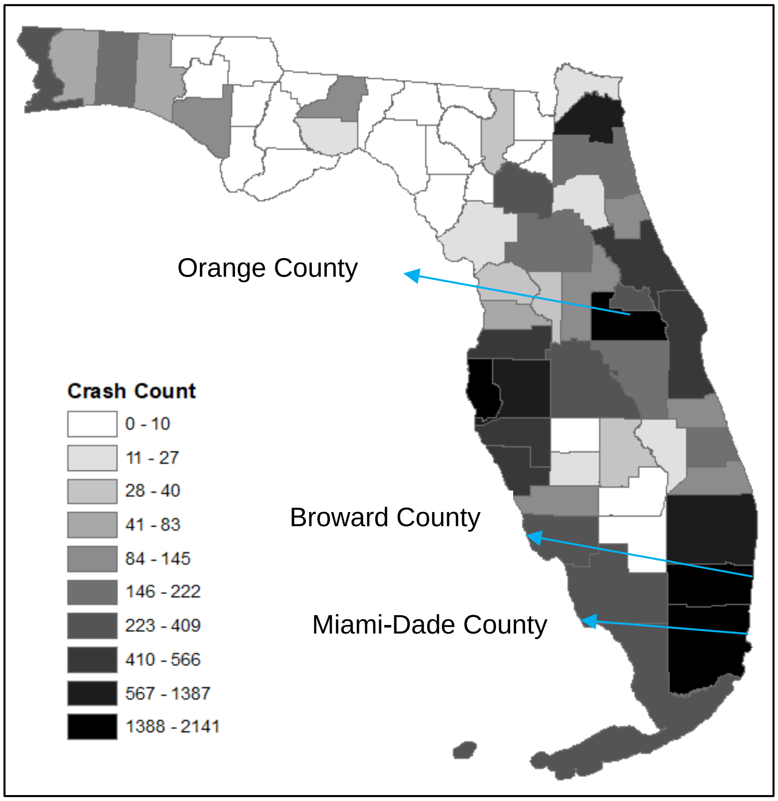

Figure 2.2 - Bicycle crash distribution in Florida

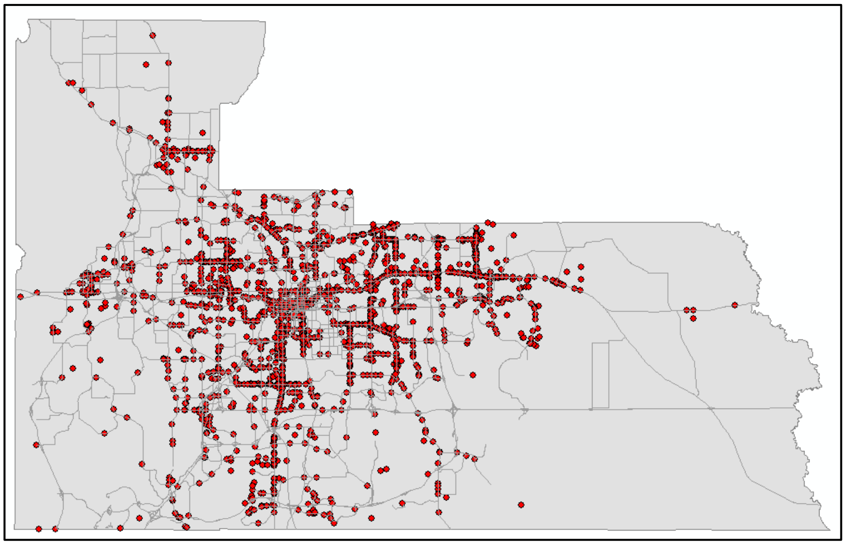

Figure 2.3 - Bicycle crash distribution in Orange County, Florida

Upon closer inspection of the crash frequency at the intersections of Orange County between 2013 and 2016, it can be noted that bicycle crashes occurred during the peak hours of 3:00 pm to 6:00 pm, as shown in Figure 2.4. Hence, more attention should be paid to the peak conditions. Winter and fall have higher rates of bicycle crashes than the summer and spring seasons. Bicycle crashes tend to increase by 10% in the winter when compared to summer. In addition, it was found that female drivers were less likely to be involved in bicycle crashes. Bicycle crashes occurred most frequently for cyclists aged between 25 and 35, as shown in Figure 2.5.

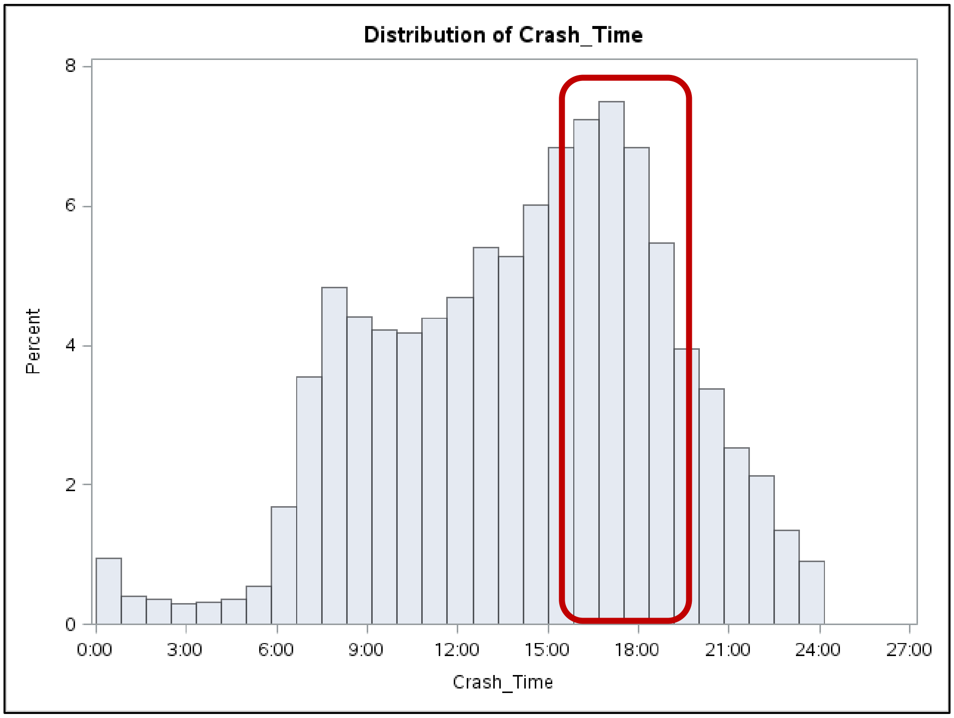

Figure 2.4 - Bicycle crash time

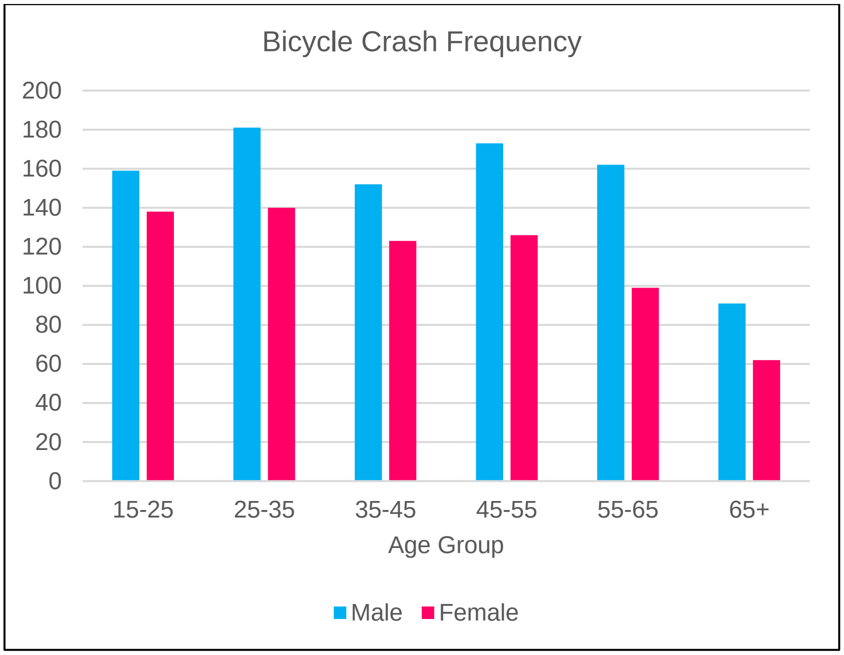

Figure 2.5 - Bicycle crash frequency for various age groups

2.2 STRAVA Data

Crowdsourced data provides the opportunity to study bicycle data in a prospective, efficient, and rigorous way. The data was collected using either GPS transponders or smart-phone applications that use GPS for recording bicycle trips on tracked routes. Specifically, in this study, STRAVA data was used since it provides a database for tracking millions of bicycle trips [36]. STRAVA data was obtained over the course of four years (2013-2016) from the Florida Department of Transportation (FDOT) Unified Basemap Repository (UBR). STRAVA is a smartphone application that tracks runners and cyclists' activities via GPS. Over 90 million users and more than 2.5 million activities tracked by GPS are uploaded every week to STRAVA [22]. This rich amount of temporal and spatial data could be used for analyzing bicycle safety at intersections. However, suspicions have been raised by some studies about the applicability of STRAVA data for representing the actual proportion of cycling activities in the overall population [23, 24, 37]. Hence, adjustments were applied in this study to overcome the skewness and the biases of the data due to the disproportionate representation of bicycle trips.

Bicycle data was obtained over the course of four years (2013-2016) from the STRAVA Metro database. Figure 2.6 shows STRAVA bicycle trips in Florida's counties. The highest number of STRAVA bicycle trips occurred in Miami-Dade, Broward, Orange, and Pinellas Counties. In addition, bicycle miles traveled (BMT) was computed for each county as the bicycle volume divided by the number of miles traveled. Figure 2.7 shows the spatial distribution of BMT. It can be noted from the figure that Miami-Dade, Broward, Orange, and Pinellas Counties have the highest BMT in Florida. Additionally, bicycle crash rate was calculated as the number of bicycle crashes divided by BMT. It was found that Orange and Pinellas Counties have the highest bicycle crash rate in Florida, as shown in Figure 2.8. Figure 2.9 shows STRAVA bicycle trips in Orange County.

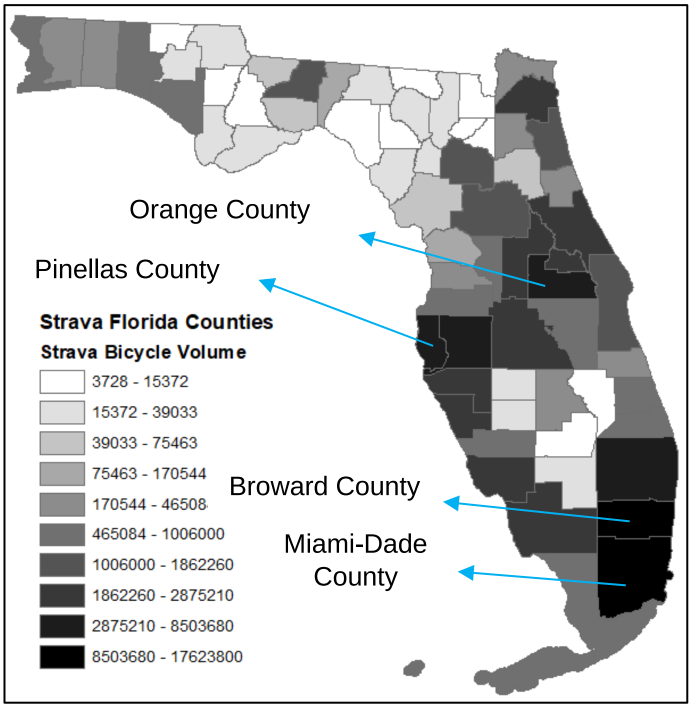

Figure 2.6 - Bicycle trip distribution from STRAVA Metro data

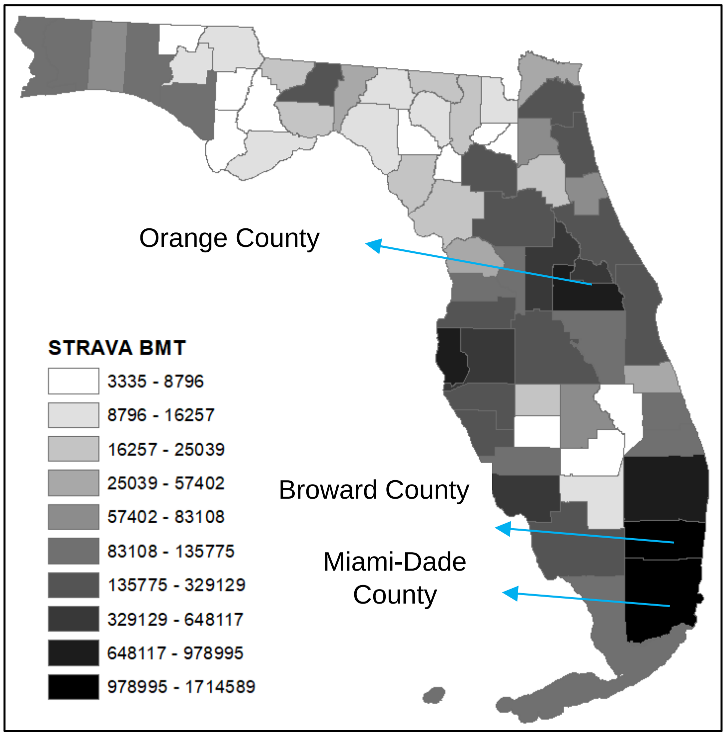

Figure 2.7 - Bicycle miles traveled from STRAVA Metro data

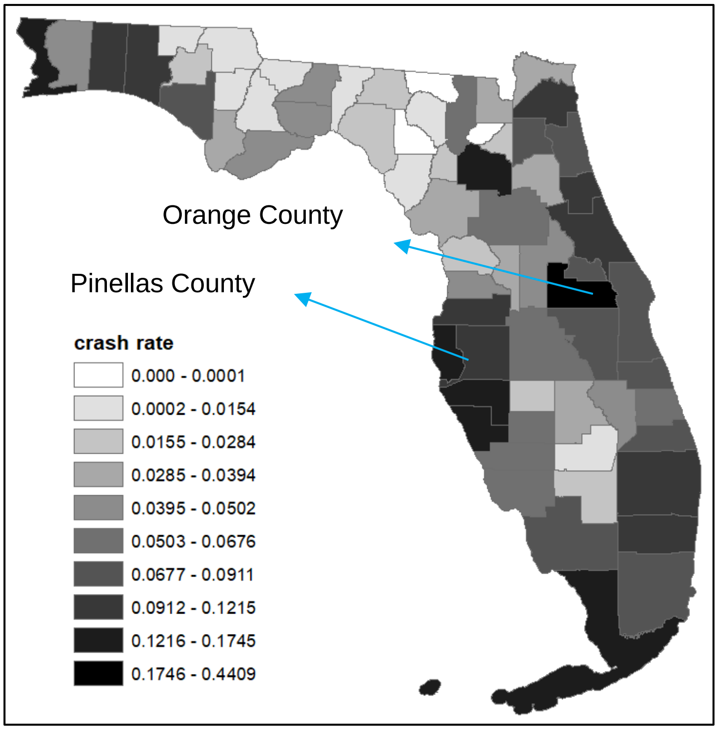

Figure 2.8 - Bicycle crash rate in Florida

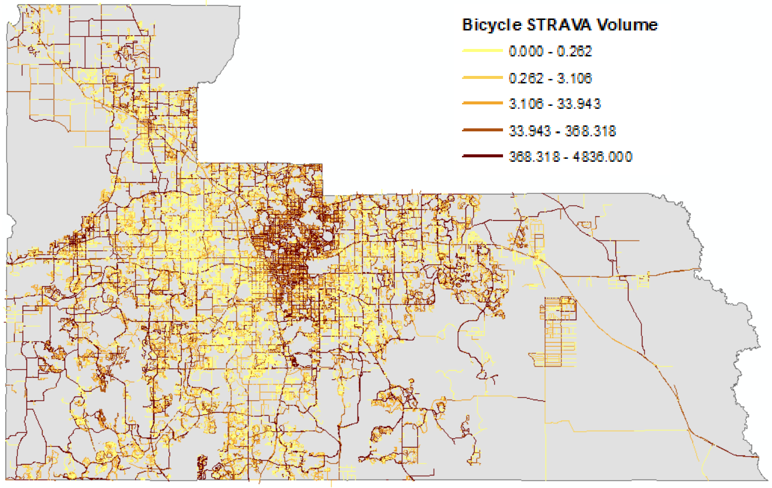

Figure 2.9 - Spatial distribution of bicycle STRAVA data in Orange County

2.3 Road Characteristics Data

Road geometric characteristics data was collected from the Roadway Characteristics Inventory (RCI) database of the FDOT. Table 2.1 shows a detailed description of the road characteristics used in the modeling. Intersection size is the perimeter of the intersection calculated from the number of lanes and the lane width of each leg. According to the FDOT, pavement condition value ranges between 0 and 5. Values between 0 and 2 imply a poor pavement condition, while values between 4 and 5 represent a higher-quality condition, indicating newer pavement condition. In addition, values between 3 and 4 reveal a good pavement condition, while a fair pavement condition occurred when the values ranged between 2 and 3. The table presents the mean and standard deviation (SD) of the continuous variables such as shoulder width, median width, sidewalk width, intersection size, speed limit, and pavement condition. It is worth mentioning that, for continuous variables, the average value of the major and minor roads was used in the analysis.

Furthermore, total entry volume (TEV) and total entry bicycle (TEB) were included in the analysis. TEV is the aggregated traffic volume of the major and minor roads in the four-legged intersections, while in the three-legged intersections, it is calculated as the aggregation traffic volume in the major road and half of the traffic volume in the minor road. Total entry bicycle is the aggregated STRAVA bicycle trips of the major and minor roads.

Table 2.1 - Road characteristics at Orange County intersections

Categorical Variables	Attributes	Percentage	
		Major road	Minor road
Signal Control System	Traffic Signal	74%	
	Stop sign	26%	
Intersection Legs	Four-leg	68%	
	Three-leg	32%	
Bike Lanes	Yes	26%	20%
	No	74%	80%
Shoulder Type	Paved	32%	29%
	Not paved	3%	5%
	No shoulder	65%	66%
Median Type	Painted	34%	46%
	Concrete	11%	19%
	Turf	7%	21%
	Curb	48%	14%
Pavement Condition	Poor	7%	9%
	Fair	10%	18%
	Good	46%	45%
	Very good	37%	28%
Road Surface Type	Asphalt	94%	98%
	Concrete	6%	2%

Road System	Principal arterial	34%	4%
	Minor arterial	32%	14%
	Collector	33%	79%
	Local	1%	3%
Sidewalk Barrier	No barrier	71%	94%
	With barrier (guardrail, parking lane, row of trees)	29%	6%
Continuous Variables		Mean (S.D.)	
		Major road	Minor road
Intersection Size (feet)		98.64 (23.42)	
Median Width (feet)		18.05 (17.74)	11.99 (9.61)
Sidewalk Width (feet)		6.07 (3.75)	4.68 (1.17)
Shoulder Width (feet)		2.52 (3.066)	2.11 (0.75)
Speed Limit (mph)		39.03 (7.76)	33.54 (7.44)

2.4 Data Adjustment

One of the problems encountered in the STRAVA data is the disproportionate representation of bicycle trips among the overall population. Previous studies found that STRAVA data is skewed towards young, male cyclists [24]. Additionally, STRAVA represents only a small portion of the overall cyclists in the real world. Jestico et al. [23] found that one cyclist from the crowdsourced data represents 51 bicycle riders in the field. Hence, in our study, two types of adjustments were determined as needed: population representation adjustment and field observation data adjustment.

2.4.1 Population Representation Adjustment

The major benefit of the data manipulation process is to create adjustment factors to be applied to the STRAVA data in order to appropriately represent the actual bicycle data at intersections. In the population representative adjustment process, factors were generated and applied to the data to adjust the percentages of cyclists for various age and gender groups. The adjustment factors were calculated based on the following formula:

$$Adjustment\ factor = (1 - (STRAVA\ proportion - Actual\ proportion)) \quad (2.1)$$

STRAVA cyclist proportions for the different age and gender groups are shown in Table 2.2. The actual cyclist proportions were calculated for each census tract based on the bicycle data of the National Household Travel Survey (NHTS). Subsequently, the adjustment factor for each census tract was generated and applied to the studied intersections in order to adjust the STRAVA data proportions.

Table 2.2 - Breakdowns of STRAVA users' age and gender in Florida

Age	Male	Female
Under 25	8.14%	12.40%
25-34	23.08%	27.39%
35-44	28.79%	25.20%
45-54	24.87%	22.55%
55-64	11.71%	10.38%
65+	3.40%	2.08%

2.4.2 Field Data Adjustment

STRAVA bicycle data was manipulated for representing the field observation data by generating adjusted TEB for the intersections of Orange County using actual observed data. A total of 171 intersections with field-observed data were randomly selected for computing the adjusted TEB for the intersections of Orange County. The observed bicycle data at the intersections of Orange County was provided by FDOT, District 5 traffic operations. Figure 2.10 shows the intersections with observed volumes. The observed data includes daily bicycle frequency for each intersection. In addition, STRAVA data was calculated for each intersection from the average number of the annual bicycle trips value for each year from 2013 to 2016 and converted to a daily value to match the observed data. A Spearman correlation coefficient of 0.72 and a P-value<0.0001 at a 95% confidence indicates a significant association between the field observed bicycle data and the STRAVA crowdsourced data. A linear regression model was utilized to determine the adjustment factor for the 481 intersections (Figure 2.11) in Orange County.

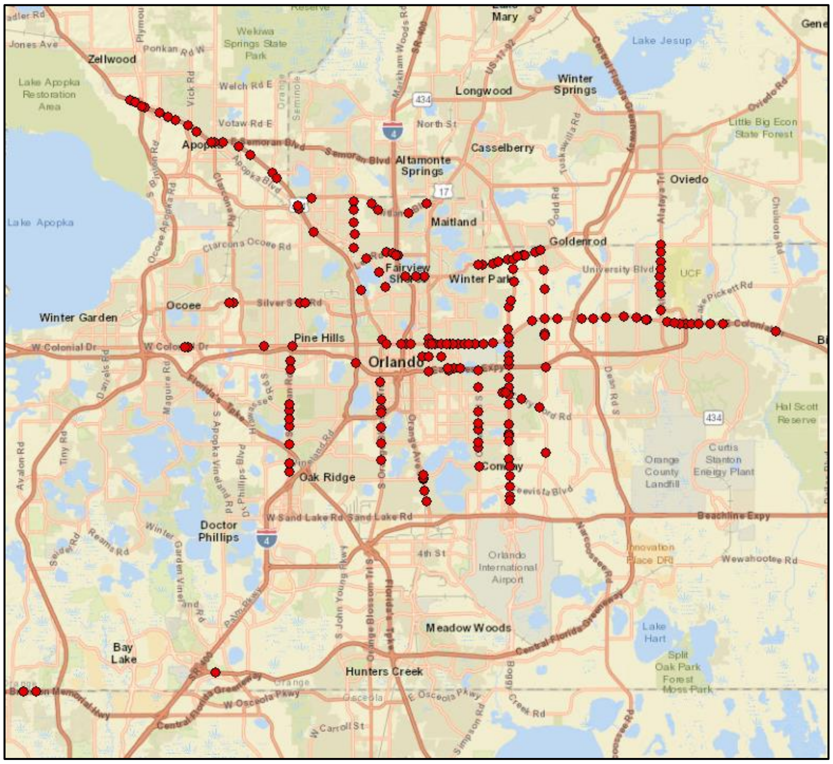

Figure 2.10 - Intersections with observed volumes in Orange County

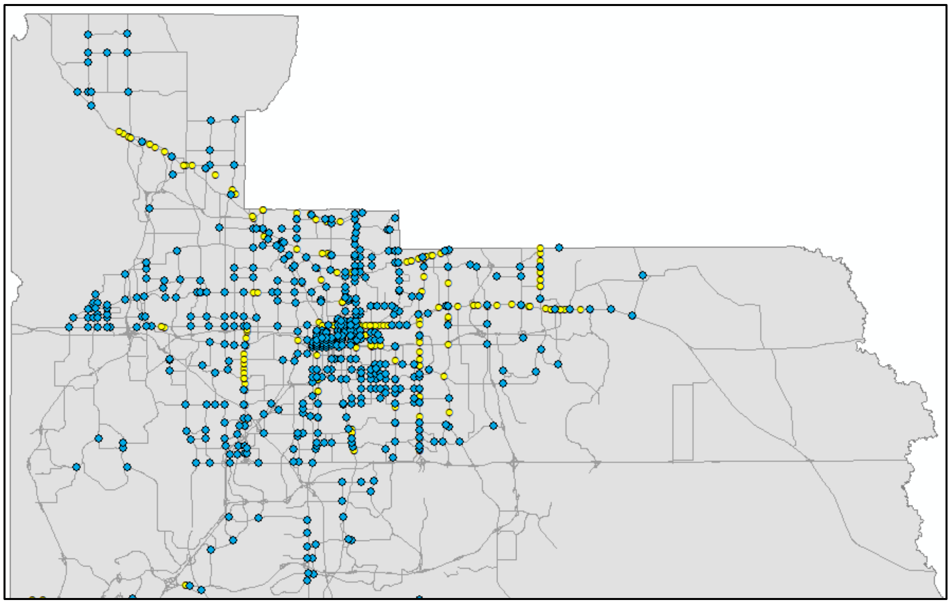

Figure 2.11 - Studied intersections in Orange County

(Note: yellow intersections represent the observed data)

The model was adopted for generating a formula to be applied to the intersections of Orange County that have no observed data. The outcome is the natural logarithm of the bicycle volume observed in the field. The results (Table 2.3) showed that several variables, including TEV (in 1000 vehicles), TEB, the ratio between TEV and TEB, and intersection size, could significantly affect the adjusted TEB.

Table 2.3 - Linear regression results for the adjusted TEB

Parameters	Parameter Estimate	Standard Error	t-value	p-value
Intercept	4.0363	0.1671	24.15	<.0001
TEV	0.0098	0.0015	6.36	<.0001
TEB	0.0143	0.0035	4.00	<.0001
Ratio	-0.0056	0.0002	-21.76	<.0001
Intersection Size	0.0021	0.0009	2.03	0.0441
Model Fit				
Adjusted R-Square	0.801			
F-value (p-value)	164.42 (<0.0001)			

The coefficient of determination (R-squared value= 0.801) indicates that the estimated model can be employed for accurately determining the adjusted TEB. Based on the results of the linear regression model, the formulation for computing the adjusted TEB at intersections is as follows:

$$Adjusted\ TEB = \exp(4.0363 + 0.0098 \times TEV + 0.0143 \times TEB - 0.0056 \times Ratio + 0.0021 \times Intersection\ Size) \quad (1.2)$$

3 Methodology

Negative binomial models were used to develop the SPFs of bicycle crashes at intersections. Safety performance functions have been a prominent tool for predicting crash frequencies and identifying the factors that affect crashes. Previous studies utilized the NB framework as a flexible approach for developing SPFs [38, 39].

Safety performance functions attempt to quantify the effect of contributing factors on bicycle crash frequencies at intersections. The bicycle crash frequency was considered as the dependent variable. Multiple road characteristics variables (i.e., pavement condition, bike lanes, etc.) served as the independent variables. Two exposure measurements, TEV and TEB, were considered as crash predictors in the model development. SAS 9.4 was used for developing the NB models. The model formulation takes the following form:

$$Y \sim NB\ (\lambda_i) \tag{3.1}$$

$$\lambda_i = \exp(\beta_0 + \beta_1\, Ln\ (TEV)_i + \beta_2\, Ln\ (TEB)_i + \beta_z\, X_i + \varepsilon_i) \tag{3.2}$$

where λ_i is the response variable (expected crash frequency) at intersection i; β0 is the intercept; β1, β2, β3, and βz represent the coefficient of independent parameters; ε is the gamma-distributed error term with a mean equal to 1 and variance α (i.e., over-dispersion parameter); X_i represents the road geometry characteristics; and β_z represents corresponding coefficients to be estimated.

4 Modeling Results

The NB models were used for identifying the optimal case for STRAVA data adjustment. The first model included the STRAVA data without adjustments. The second model was developed for STRAVA data with a population representation adjustment. The third model that was estimated included the STRAVA data with field data adjustment. The fourth model utilized both population representation and field observation data adjustments. Table 4.1 shows the results of the models and the comparison of STRAVA bicycle data cases. Five goodness-of-fit measures were used: the Akaike information criterion (AIC), Bayesian information criterion (BIC), root mean squared errors (RMSE), mean absolute deviation (MAD), and percent mean absolute deviation (PMAD). The AIC and BIC estimate the quality of the model. Better models have smaller AIC and BIC values. The RMSE is the sum of the squared error divided by the number of observations, and MAD is the sum of the absolute deviations over the number of observations. Lastly, PMAD is calculated based on the sum of absolute deviations over the sum of absolute observed values. The equations of the goodness-of-fit measures are shown as follows:

$$AIC = 2 \times k - 2 \times \ln(\hat{L}) \tag{4.1}$$

$$BIC = \ln(N) \times k - 2 \times \ln(\hat{L}) \tag{4.2}$$

$$RMSE = \sqrt{\sum_{i-1}^{N} (y[i] - \hat{y}[i])^2 / N} \tag{4.3}$$

$$MAD = \sum_{i-1}^{N} |y[i] - \hat{y}[i]| / N \tag{4.4}$$

$$PMAD = \sum_{i-1}^{N} |y[i] - \hat{y}[i]| / \sum_{i-1}^{N} |y[i]| \tag{4.5}$$

where k is the number of estimated parameters in the model; $\hat{L}$ is the maximum value of the likelihood function for the model; $y[i]$ is the observed value of i; $\hat{y}[i]$ is the predicted value of i; and N is the number of observations.

The results of the goodness of fit indicated that STRAVA data with adjustment could consistently provide better performance than data without any adjustment. Applying both field and population representation adjustments showed the best performance, which minimized the values of AIC and BIC. Also, the lowest values of MAD, RMSE, and PMAD in the case of STRAVA data with both adjustments imply better performance than the other cases. Therefore, it is concluded that STRAVA data should be adjusted for proper representation of real-life bicycle volume.

Table 4.1 - SPF results for all studied cases

		STRAVA without Adjustment		STRAVA with Population Adjustment		STRAVA with Field Adjustment		STRAVA with Both Adjustments	
Parameters	Attributes	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.
Intercept		-11.457*	1.185	-11.392*	1.170	-16.041*	1.615	-16.867*	1.500
Log TEV		0.766*	0.124	0.730*	0.123	0.498*	0.132	0.434*	0.128
Log TEB		0.085**	0.048	0.103*	0.047	0.899*	0.208	1.016*	0.179
Intersection Size		0.007*	0.003	0.009*	0.003	0.006*	0.003	0.006*	0.003
Signal Control System	Signalized (vs. Stop)	0.626*	0.252	0.615*	0.251	0.706*	0.248	0.672*	0.245
Number of Legs	Four (vs. Three)	0.321*	0.159	0.301**	0.157	0.289**	0.155	0.260**	0.152
Bike Lane	Yes (vs. No)	-0.411*	0.146	-0.401*	0.145	-0.379*	0.143	-0.338*	0.141
Sidewalk Width		-0.070*	0.028	-0.071*	0.027	-0.074*	0.027	-0.072*	0.026
Median Width		-0.013*	0.005	-0.012*	0.005	-0.011*	0.005	-0.009**	0.005
Speed Limit		0.030*	0.010	0.030*	0.009	0.028*	0.009	0.029*	0.009
Over-dispersion		0.261	0.103	0.231	0.101	0.179	0.089	0.136	0.082
Model Fit									

Log Likelihood	-481.8657	-478.9470	-471.5531	-464.9226
AIC	985.7314	979.8940	965.1062	951.8452
BIC	1031.5278	1025.6904	1010.9027	997.6417
RMSE	1.7345	1.6866	1.6501	1.6097
MAD	1.9163	1.8974	1.8647	1.8392
PMAD	0.9077	0.8988	0.8833	0.8712

* Significant at 95% confidence interval; ** Significant at 90% confidence interval

Based on the best model (i.e., STRAVA with both population representation and field observation data adjustments), it is concluded that TEV, TEB, intersection size, signal control type, number of intersection legs, bike lanes, sidewalk width, median width, and speed limit are the significant factors that affect bicycle crashes at the intersections of our study area. Closer inspection of the table revealed that the two exposure variables (TEV and TEB) were significant at a 95% confidence interval and positively associated with bicycle crashes. Hence, bicycle crashes increased significantly at intersections with denser motorist and bicyclist traffic. The results of the model revealed that there is a significant positive association between intersection size and bicycle crashes. As the intersection size increases, the bicycle crashes increase significantly. Signal type control was found to significantly influence the bicycle crash count. The results intuitively suggest higher bicycle crashes at signalized intersections due to higher bicycle volume. This finding confirms the recent FDOT study, which found that signalized intersections have higher injury and total bicycle crashes than unsignalized intersections by 12% and 16%, respectively [35]. The results also showed that the number of intersection legs had a significant impact on the bicycle crashes. Three-legged intersections tend to have fewer bicycle crashes than four-legged intersections. This result may be explained by the fact that three-legged intersections have fewer turning conflicts [40]. Other than the number of legs, it is apparent from the model results that the bike lanes have a significant negative impact on bicycle crash incidents at intersections. This finding confirmed recent studies that bike lanes influenced the likelihood of bicycle crashes occurring [10, 25, 41]. The results also uncovered that bicycle crash frequency decreased with an increase in sidewalk width. It was also found that there is a significant association between median width and bicycle crashes. An increase of the median width decreases the likelihood of bicycle crashes at intersections. Concerning speed limit, it is worth mentioning that bicycle crashes occur significantly less often at intersections with lower speed limits. Lastly, it was found that several variables, such as median type (e.g., painted, curb), surface type (e.g., concrete, asphalt), road system (e.g., principal arterial, local), sidewalk barrier existence, shoulder type (e.g., paved, not paved), shoulder width, and pavement condition (e.g., fair, good), have no significant effect on bicycle crashes at intersections. In general, the SPFs developed by the NB models provide a better understanding of the key factors affecting bicycle crashes at intersections, such as motorist traffic volume, bicycle volume, road geometry, and bicycle infrastructure. The model results provide recommendations for agencies and researchers about how bicycle infrastructure design innovation can have a significant impact on bicycle crashes at intersections.

Furthermore, the relation between TEB and bicycle crash risk was illustrated, as shown in Figure 4.1. Bicycle crash risk was calculated as the number of bicycle crashes divided by the TEB for each intersection. The crash risk then was ranked in ascending order. It is apparent from Figure 4.1a that when the bicycle volume increases, the ranking of crash risk decreases, which indicates lower bicycle crash risk occurrence, namely, the safety-in-numbers effect. This result may be explained by the fact that drivers are more cautious at intersections with many bicyclists (e.g., residential areas, school zones). A Spearman rank correlation test was conducted, and it was found that the ranking by bicycle crash risk had a high statistical correlation (0.78, $p < 0.0001$) with TEB. Moreover, the potential for safety improvement (PSI), or the expected excess crash frequency, was calculated as a measure of intersections that have higher bicycle crashes than those with similar features [42-44]. The formula of PSI is presented as follows [43, 44]:

$$PSI = N_{expected} - N_{Predicted} \tag{4.6}$$

$$N_{expected} = W \times N_{predicted} + (1 - W) \times N_{observed} \tag{4.7}$$

$$W = \frac{1}{1 + \propto \times N_{Predicted}} \tag{4.8}$$

where $N_{expected}$, $N_{Predicted}$, $N_{observed}$ are the expected, predicted, and observed number of bicycle crashes; W is the empirical Bayes weight; and $\propto$ is the over-dispersion parameter of the SPF. If the PSI is negative, the intersection is considered safe since it experiences fewer bicycle crashes than other intersections with similar characteristics. Alternatively, the intersection with a positive PSI value is considered dangerous, as it experiences more bicycle crashes than similar intersections [43, 44]. In this study, 31% of intersections are considered dangerous based on positive PSI values. Figure 4.1b represents the relationship between TEB and the ranking by PSI, in ascending order, for all studied intersections. The figure shows that there is no relation between TEB and PSI, which indicates that the potential improvement of crash frequency is not associated with bicycle volume. In addition, a Spearman rank correlation test was conducted, and it was found that the ranking by PSI had no statistical correlation (0.047, p=0.299) with TEB.

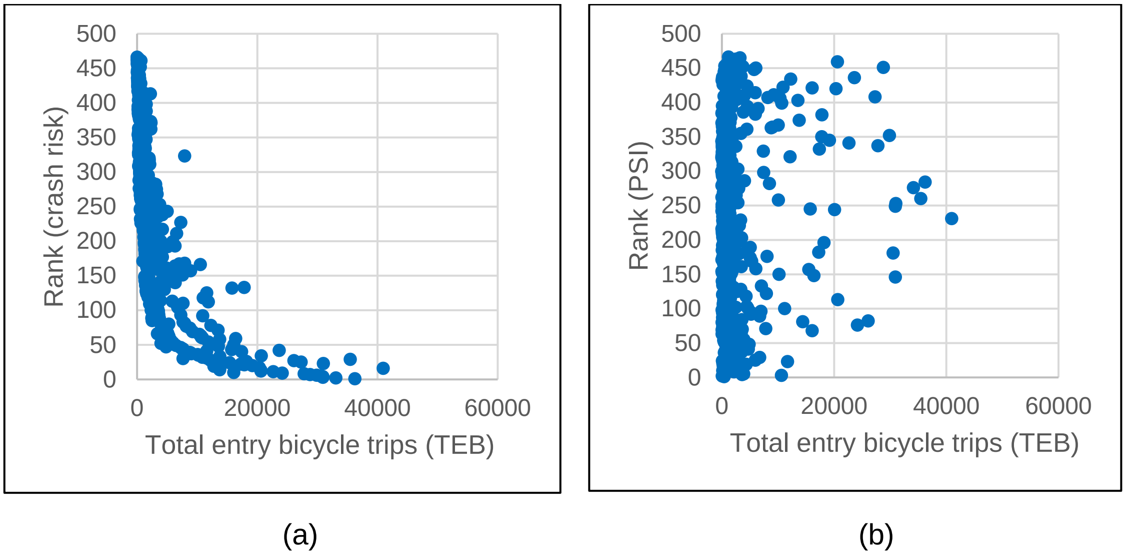

Figure 4.1 - The relationship between TEB and crash risk at intersections

5 Conclusions and Recommendations

Bicycles have been considered a sustainable, low-cost, and energy-efficient mode of transportation in many countries throughout the world. Previous literature has prompted more bicycle-related studies in order to improve cyclist safety and provide recommendations related to better bicycle infrastructure for promoting bicycle use.

The analysis in this study was undertaken by using crash data and bicycle crowdsourced STRAVA data at the intersections of Orange County in Florida over the course of four years (2013-2016). Previous studies concluded that STRAVA bicycle volume has a significant association with field bicycle volume; however, it represents only a sample of the overall cyclists in the real world [23, 45]. Hence, multiple adjustments were applied in order to overcome the disproportionate representation of STRAVA data. A linear regression model was developed to predict the adjusted TEB based on observed bicycle data. The results of the model demonstrated that traffic volume, bicycle volume, ratio between TEV and TEB, and intersection size are all factors that have a significant impact on the adjusted TEB. Different cases were defined, including STRAVA without adjustment, STRAVA with population representation adjustment, STRAVA with field adjustment, and STRAVA with both population representation and field adjustments. Comparing the studied cases suggests that it is necessary to apply both population representation and field data adjustments, as they were shown to have the best model performance (i.e., AIC, BIC, MAD, PMAD, and RMSE).

Safety performance factors were developed utilizing NB models. It was found that both traffic volume and bicycle volume, which are exposures, have significantly positive effects on bicycle crashes. In line with previous studies, bicycle crash rates decreased with an increase in bicycle volumes, namely, the safety-in-numbers effect [12, 49, 50]. A set of geometric factors, including bike lanes, intersection size, signal control system, number of intersection legs, sidewalk width, pavement condition, median width, and speed limit, were found significant in the model. With better bicycle exposure used in this study, it is expected that more proper effects of the geometric factors could be identified. Significantly positive association could be found between the existence of bicycle lanes and reduction of bicycle crashes. Several studies have confirmed the effect of bicycle lanes on cyclist safety [9, 18, 41, 46-48]. Another finding was that signalized intersections are more likely to have higher rates of bicycle crashes than unsignalized intersections due to high bicycle volume. Similarly, three-legged intersections tend to have fewer bicycle crash frequencies than four-legged intersections.

It is recommended that the identified geometric factors be included in simulation studies, as it is expected that the studies could help further explain why the identified factors have significant effects on the occurrence of bicycle crashes at intersections. For example, a simulation study could be conducted to explore drivers' reactions and behaviors when they meet a bicyclist at an intersection with and without bike lanes. In general, the present study contributes to the growing body of research that crowdsourced data could be a good source of bicycle exposure for bicycle crash analysis at intersections. In addition, STRAVA data adjustments proved to provide better model performance of bicycle safety performance analysis.

This study can help transportation agencies by identifying efficient ways to determine bicycle volume and by identifying critical factors for enhancing bicycle safety and improving bicycle infrastructure at intersections. Transportation engineers and planners should focus on improving road geometry characteristics to further enhance bicycle safety at intersections (e.g., improving pavement condition, considering low speed limits, and having a sufficient sidewalk width, shoulder width, and median width). Policy-makers might consider the recommendations about bicycle infrastructure and road geometry for improving cyclist safety. Such policies could also encourage bicycle use as a safe, economical, energy-efficient, and sustainable mode of transportation.

The research presented opens the door to ample future opportunities. The findings of this study represent a step towards improving bicycle safety using crowdsourced data. This contribution could be used when calculating bicycle crash modification factors at intersections. Future studies could also be undertaken for developing SPFs for pedestrians using crowdsourced data. It is also worth noting that further studies should be conducted to explore how this work could be replicated in different cities or across large regions.

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