Accident Analysis and Prevention 130 (2019) 54–61

Contents lists available at ScienceDirect

Accident Analysis and Prevention

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

A mixed methods investigation of bicycle exposure in crash rates

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ARTICLE INFO

Article history:
Received 4 September 2016
Received in revised form 19 January 2017
Accepted 3 February 2017
Available online 1 March 2017

Keywords:
Bicycle crash rates
Bicycle exposure
Corridor analysis

ABSTRACT

Crash rates are an essential tool enabling researchers and practitioners to assess whether a location is truly more dangerous, or simply serves a higher volume of vehicles. Unfortunately, this simple crash rate is far more difficult to calculate for bicycles due to data challenges and the fact that they are uniquely exposed to both bicycle and automobile volumes on shared roadways. Bicycle count data, though increasingly more available, still represents a fraction of the available count data for automobiles. Further compounding on this, bicycle demand estimation methods often require more data than automobiles to account for the high variability that bicycle demand is subject to. This paper uses a combination of mixed methods to overcome these challenges and to perform an investigation of crash rates and exposure to different traffic volumes.

1. Introduction

Although there is an increasing number of separated bicycle facilities being constructed across the United States, the vast majority of bicycle travel routes are still shared with vehicular traffic. Bicycles are a unique mode in that they are a vulnerable non-motorized mode, but often share the same space with automobiles. As a result, bicycles are essentially doubly exposed to risk both as a bicyclist, but also as a roadway user. This presents a challenge to safety analysts attempting to determine where improvements should be located or studying the effectiveness of new facilities. This further affects bicycle ridership as safety, and the perceived lack of, is one of the largest barriers keeping potential bicyclists off the road (Sanders, 2013a,b). The importance of properly assessing roadway safety cannot be stressed more greatly, not only to improve roadways for current bicyclists, but to also continue encouraging new cyclists onto the roads.

Roadway safety analysis can be accomplished in a multitude of methods varying in complexity and applicability. One of the most fundamental tools to the industry is crash rates. Crash rates are a method of normalizing the number of crashes to account for factors that would contribute to an increase in frequency, but not necessarily affect the actual safety. Crash rates enable researchers and professionals to compare across multiple locations to statistically highlight any commonalities between specific elements that may be causing or reducing crashes. Recently there has been a growing number of studies focusing on bicycle safety in particular, investigating environmental, behavioral, or demographic factors contributing to crashes (Hamann and Peek-Asa, 2013; Jiménez-Mejías et al., 2016; Park et al., 2015; Poulos et al., 2015; Martínez-Ruiz et al., 2015; Abdel-Aty and Pande, 2007).

The most typical normalizer used by departments of transportation is average annual daily traffic (*AADT*) (MassDOT, 2016; FHWA, 2011). However, this is challenging for bicycles as bicycle transportation until relatively recently has been regarded as a recreational or non-essential mode of transportation in the United States. Decades of this unfortunate status has resulted in a substantial lack of bicycle count and crash data in most U.S. cities. To date, most bicycle counts are short term counts and must be adjusted to a longer period, such as annual average, to be used in a crash rate. This presents a further challenge as bicycle usage is highly variable due to a multitude of environmental, social, and temporal factors. This variability makes it extremely difficult for researchers and professionals to accurately estimate or impute data spatially or temporally. In addition to challenging data adjustments and lack of data overall, bicyclists are also exposed as a mode of their own as well as to motorized vehicles on shared roads. This causes simple normalizing crash rate equations to result in a disproportionately high or low crash rate if only one traffic volume is accounted for. This is an issue that requires research attention.

An important achievement in the understanding of roadway safety is the modeling of crash probabilities. Many studies have shown that crash frequency distributions are non-linear and can be modeled by a mathematical function (Joshua and Garber, 1990; Wood, 2005, 2002; Lord and Persaud, 2000; Lord et al., 2005; Ye et al., 2013). The purpose of modeling this is to construct prediction models for crash probability functions. This area has received a fair

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https://doi.org/10.1016/j.aap.2017.02.004
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amount of attention by researchers attempting to improve or simplify the process (Abdel-Aty and Radwan, 2000; Chin and Quddus, 2003; Polus and Cohen, 2012; Qin et al., 2004; Avelar et al., 2015; Johansson, 1996; Ma et al., 2008). Most models utilize some means of linearizing the frequency with Poisson, negative binomial, and other logarithmic or non-linear functions. Although these studies mainly focus on motorized modes, the fundamental statistics are expected to be applicable for bicycles.

In the past, roadway safety was primarily "spot based", meaning that safety improvement efforts were retroactively applied to specific locations after enough crashes had occurred. Today with advances in computerized mapping technology and geographic information systems (GIS), crashes can be easily geolocated and investigators can now perform a multitude of analyses, such as spatial densities, probabilities, regression, and other logistic models (Wang et al., 2015; Cai et al., 2016; Chen, 2015; Chin and Quddus, 2003; Hankey et al., 2012). This not only greatly extends the research capabilities, but fundamentally enables the development of systemic solutions that can be applied to roads preventing accidents before they occur. This is especially important for bicycling to not only improve conditions for current bicyclists, but to make bicycling a less stressful experience and attract more people to bicycling.

This study addresses and incorporates these concepts by utilizing 30 short term counts spatially and temporally distributed in the City of Cambridge as well as two continuous counters. These short term counts were collected at varying locations, times, and dates and need to be adjusted to a comparable rate, such as annual average daily bicycles (*AADB*). Typically this is accomplished using adjustment factors established using a minimum of five continuous counters across the city. Unfortunately with only two counters this is not ideal, furthermore one of the continuous counters collected less than one full year of data. Not only is this a challenge from an estimation standpoint, but the 32 count locations represent a small fraction of the several hundred intersections and midblock segments across the city where crash data is available. This severely limits any attempt at crash rate analysis due to the small number of locations where crash frequencies can be normalized, ultimately hiding potentially dangerous locations due to sparse data. In order to further extend the available data, novel new analysis methods are needed. This paper proposes a mixed methods framework accounting for the challenges associated with bicycle crash analysis. It is the intent that this will allow future studies to better understand bicycle crash risks on shared roadways.

2. Data and methodology

The data utilized in this paper consists of three components, spatial roadway network, bicycle and vehicle traffic counts, and crash data. With recent advances in computerized mapping, or geographic information systems (GIS), spatial roadway network data have become increasingly more available to the public. This spatial data can then be used as a bridge between the different data, allowing for more in depth analyses. Furthermore, this spatial data allows for limited data, such as bicycle counts, to be expanded using the network.

The bicycle crash records used in this paper all involved automobiles and did not contain hospital records for other crash types, such as individual bicycles, bicycle-bicycle, or bicycle-pedestrian crashes. Although there are likely millions of minor bicycle crashes and near misses that occur each year, they typically go unreported. This is due to the fact that most vehicle crashes are reported for insurance purposes. Unless a vehicle is damaged or a bicyclist seriously injured, it is not uncommon for a bicyclist to be injured and even treated by a hospital, without have any record of the crash reported.

This crash analysis framework consists of three basic steps:

(1) Annual average daily volume estimation: adjust short term counts to the annual average daily volume level using factors from continuous counters.
(2) Corridor assignment: assign crash locations and annual average daily volumes to corridors using spatial network data.
(3) Crash analysis: calculate a hybrid crash rate based on the assigned corridor volumes for both bicycles and automobiles.

2.1. Bicycle crash rate

In general, the purpose of calculating crash rates is to normalize crash data to compensate for exposure to differing traffic volumes. The expected results are that locations of similar risk, but different traffic volumes will result in similar crash rates. Under this assumption we would expect an unbiased plot of rates versus volume which can then be analyzed against other factors.

A crash rate can either be calculated at a point such as an intersection, or along a linear segment such as a midblock segment or rural road. In this paper, only point based rates are calculated due the limited number of midblock crashes in the data. The only difference being the extra level of normalization based on roadway length. Typically, crash rates are calculated using the common rate Eqs. (1) and (2). These equations, or variations of, are commonly used by both researchers and the professional industry (American Association of State Highway and Transportation Officials, 2010; FHWA, 2011; MassDOT, 2016). This paper directly adapts the crash rate equations for bicycles by simply replacing vehicle volume and crashes with bicycle volume and crashes. Typical crash rates are determined by the equation

$$R = \frac{1,000,000 \cdot A}{365 \cdot V} \tag{1}$$

where R, crash rate in crashes per million vehicles; A, average number of crashes per year; V, average volume of vehicles per day, or average annual daily vehicles (*AADT*).

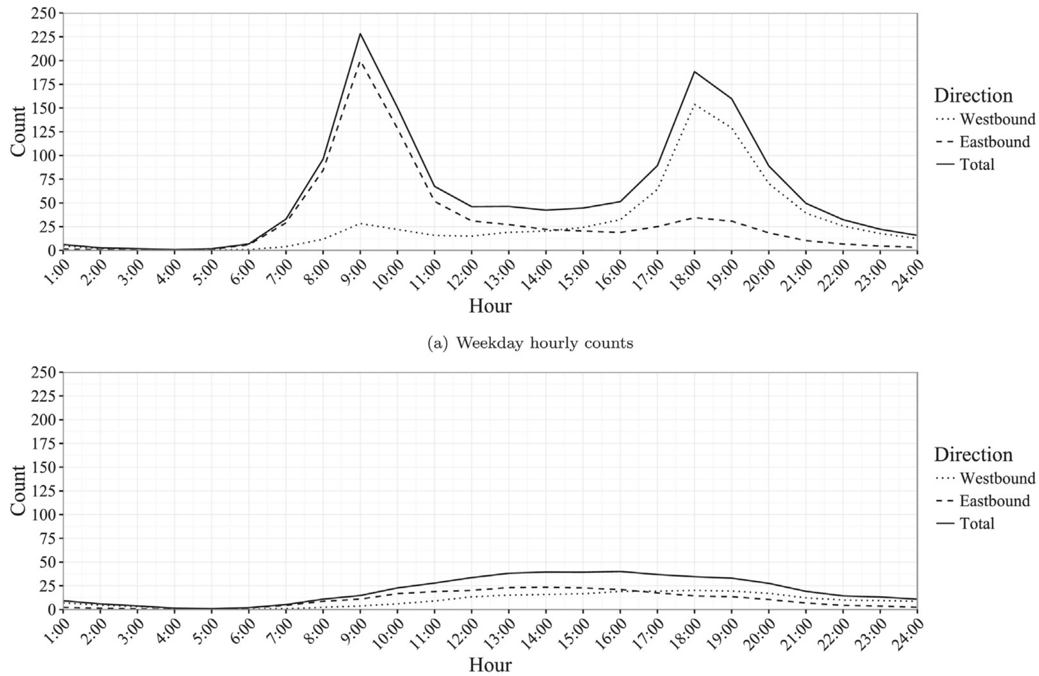
Unfortunately, these crash rate equations only account for one volume of exposure. In order to compensate for the two volumes that bicycles are exposed to, an equation that accounts for both volumes is necessary. By "nesting" one crash rate equation within the other, a new equation is developed that accomplishes this. This results in Eq. (2) with a squared constant and multiplied volumes. The proposed crash rate equation is

$$R_{dual} = \left(\frac{1,000,000}{365}\right)^2 \cdot \frac{A}{V_{auto} \cdot V_{bike}} \tag{2}$$

where R_{dual}, crash rate in crashes per million vehicles; V_{auto}, average volume of automobile traffic per day, or average annual daily vehicles (*AADT*); V_{bike}, average volume of bicycle traffic per day, or average annual daily bicycles (*AADB*).

2.2. Bicycle traffic volume estimation

In order to obtain annual average daily counts (*AADB*), the short term manual peak-hour counts need to be adjusted to the annual average level. This is due to the fact that much like automobile volume, bicycles do not arrive at a constant rate, shown in Fig. 1(a) and (b). Moreover, bicycle demand varies depending on the day of week. In this paper, adjustment is accomplished using a mixed methods approach by first adjusting to the monthly average daily count (*MADB*) with conventional adjustment factoring methods, then further adjusting to the *AADB* level using a sinusoidal model of seasonal demand.



(a) Weekday hourly counts

(b) Weekend hourly counts

Fig. 1. Average daily continuous bicycle counts on Broadway Eco-Totem counter.

2.2.1. Adjustment factors

The factors are calculated as recommended in the Federal Highway Administrations Traffic Monitoring Guide for non-motorized traffic for adjusting bicycle counts (El Esawey, 2014; El Esawey et al., 2013; Nordback et al., 2013; Federal Highway Administration, 2013). The general equation consists of factors for time of day (*TOD*) and day of week (*DOW*) based on the proportion to the annual average daily bicycle count (*AADB*). The adjustment to *MADB* is then accomplished using Eq. (3).

$$MADB_t = H_f \cdot D_f \cdot C \tag{3}$$

where $MADB_t$, monthly average daily bicycle count (*MADB*), in bicycles/day for month t; H_f, hourly factor = *AADB*/average hourly bicycles counted in that hour; D_f, day of week factor = *AADB*/average daily bicycles counted on that day of the week; C, peak hour bicycle traffic count.

2.2.2. Sinusoidal model

The adjustment from a monthly average (*MADB*) to an annual average (*AADB*) is typically accomplished using conventional adjustment factoring methods with factors representing each individual month. However, an accurate estimate would require five calibration locations, which is more than the two continuous count locations that were available in Cambridge, MA. Although the two continuous counters provide sufficient daily counts to establish time of day (*TOD*) and day of week (*DOW*) adjustment factors, the limited number of locations severely weakens the accuracy at the monthly level. An alternative method is to utilize a sinusoidal model of bicycle demand (Fournier et al., 2017). Rather than using many individually averaged adjustment factors for each month, the sinusoidal model assumes a sinusoidal pattern of seasonal bicycle demand and models this pattern using a sine function.

Once at the *MADB* level of estimation, the sinusoidal function in Eq. (4) can then estimate the *AADB* based on the month that the sample was collected. This is accomplished by calibrating the function using the α factor. α is the calibration factor for the sinusoid which determines the seasonal sensitivity of a location, accounting for the change in cyclist count between summer and winter. A higher α would result in a larger seasonal difference and a lower α would result in a smaller seasonal difference in cycling counts. The α can be calculated using Eq. (5) from two short term counts representing the maximum and the minimum monthly *ADB*. Since sinusoids start with the midpoint between crest and trough at $t = 0$, ϕ is a constant representing the horizontal shift of the sinusoid where $\phi = 0$ results in a crest at $t = 3$. For example, a desired crest in July ($t = 7$) would require a $\phi = 4$. Once the α is calibrated using continuous counters, the previously estimated *MADB* can then be used to calculate *AADB* at each location from Eq. (4). The reverse of this process demonstrates the model fit by solving the equation for $MADB_t$ and varying t as shown in Fig. 2.

$$AADB = \frac{MADB_t}{\alpha \cdot \sin\left(\frac{\pi}{6}(t - \phi)\right) + 1} \tag{4}$$

$$\alpha = \frac{MADB_{Max} - MADB_{Min}}{MADB_{Max} + MADB_{Min}} \tag{5}$$

where *AADB*, average annual daily bicycle count, in bicycles/day; ϕ, horizontal shift in months with the default crest at $t = 3$ when $\phi = 0$, or $\phi = t_{crest} - 3$; α, calibration factor for seasonal sensitivity.

2.3. Count data

In this paper the crash rates of bicycles are calculated using volumes for both bicycles and motorized vehicles. The motorized vehicle count data was obtained from MassDOT (Commonwealth of Massachusetts, 2014) as average annual daily traffic counts (*AADT*), collected in 2012. This *AADT* data required no adjustment as it is already at the annual level, meaning it represents the daily average for a whole year. However, average annual daily bicycle volumes (*AADB*) are far more sensitive to seasonal weather patterns and require more in depth estimation procedures.

The bicycle count data is composed of two types of data; manual peak hour counts and two continuous counts from two permanent counting stations. Two sets of manual count data were used, one conducted by the City of Cambridge at 17 locations and another

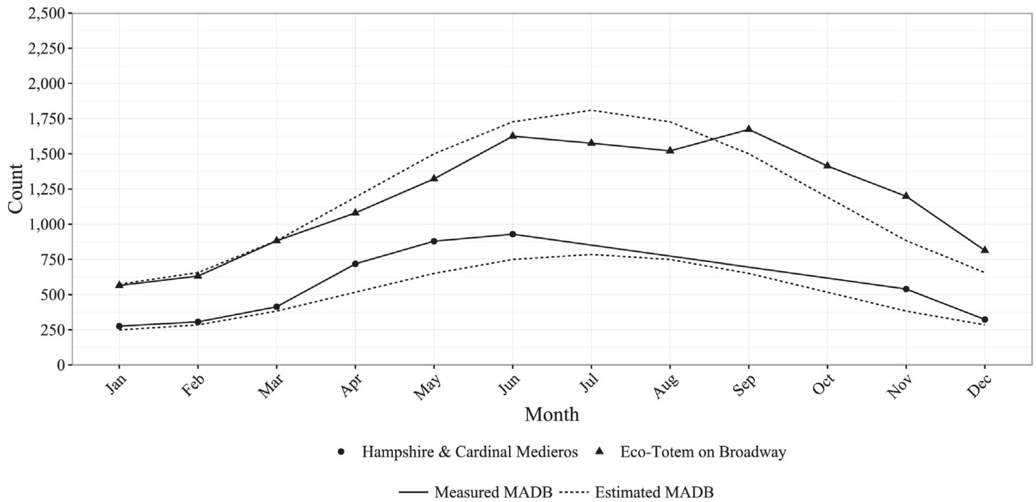


Fig. 2. Monthly ADB and sinusoidal estimate.

by the Boston Metropolitan Planning Organization at 11 locations. Continuous count data were collected from two locations in Cambridge, one from an Eco-Totem station on Broadway located in front of the Volpe Transportation Center, and another at the intersection of Hampshire Street and Cardinal Medeiros Avenue.

The permanent counter located at Hampshire Street and Cardinal Medeiros Avenue counted bicycles 24 h a day in 15-min increments from November 2013 to June 2014. The Eco-Totem counter collected data at the same increment, but from July 2015 to July 2016. The peak hour counts conducted by the City of Cambridge are simply a total count of bicycles within a 2 h period. The counts were collected for three days on September 11th to 13th, 2012. For each of these three days a bicycle count was conducted in 2-h sessions from 7:30 AM–9:30 AM and 5:00 PM–7:00 PM. The Boston Metropolitan Planning Organization's counts were conducted between the years of 2009 and 2014 in 15-min increments and vary in length from 1 to 4 h long, but all were taken during either morning, afternoon, or both peak hours. If multiple peak hours or multiple days were recorded, the estimated *MADB*'s were averaged into a single estimate.

The year that bicycle count data were collected varied from location to location. Ideally all data would be consistently from the same years across all locations, but unfortunately, bicycle data is often scarce and incomplete. For the purpose of this study, the researchers allowed for a wide range of count years in order to have a larger set of count locations. To account for the temporal differences, bicycle count data were adjusted to 2012 levels to match the year that the vehicular *AADT* were collected which is also within the 2011 to 2014 range of crash data years used in this study.

2.4. Bicycle crash data

The crash data used for this experiment consist of 622 bicycle-vehicle crashes that were reported and recorded between 2011 and 2014 in Cambridge, Massachusetts. These data were made available by the UMass Safety Data Warehouse. Each of the crashes contained geospatial coordinates enabling data to be plotted onto a map of the City of Cambridge and then subsequently matched to the locations where count data are available.

2.5. Corridors

This paper utilizes known major bicycle routes, or "corridors" where available bicycle demand data can be extended across. Although Cambridge boasts a fairly dense and complex urban road network, many of these streets lack bicycle facilities or are minor residential side streets. It can be assumed that cyclists will be concentrated along the major cycling routes. Where two or more count locations along a "corridor" have similar daily counts, it can be assumed that all intersections and road segments between these points share the same traffic flows of cyclists. This way, locations with bicycle demand data is greatly extended from the initial 30 intersections to approximately 167 intersections. Although this method admittedly lacks in precision, it opens up a much larger sample set of crash locations to be analyzed.

The corridors in Cambridge, MA were selected based on several criteria: (1) Known bicycle routes, such as ones that exhibit bicycle facilities or high bicycle counts, (2) interaction with vehicles (i.e. off-street paths were excluded), (3) availability of count and crash data along corridors. A map of count locations, corridors, and crashes are shown in Fig. 3. Multiple count locations on corridor are averaged and the final corridor *AADB* is then attributed to all locations along that route for crash rate analysis.

3. Results

3.1. Crash frequency

In an exploratory attempt to uniformly determine the crash frequency distribution across Cambridge, MA, the city was divided into a grid of 100 by 100 square meter areas in which all 622 crashes from the four year period were summed per grid cell. The results of this are shown in Fig. 4 with an appreciable non-linear trend, much similar to the non-linear distributions found in most automobile crash studies. Although this brief analysis does account for any location specific factors, the distribution shows that many of the traditional analysis methods can be applied to bicycles. Furthermore, it is apparent that the crashes are concentrated along particular streets, many of which were selected as study corridors in Fig. 3 based on available count data. Although the Cambridge street network is fairly dense and complex, it is not surprising that cyclists are concentrated along central routes, especially where bicycle facilities are present.

3.2. Traffic volume

In many bicycle safety calculations, *AADT* is used in lieu of *AADB* in calculating a crash rate. This is often founded on the assumption

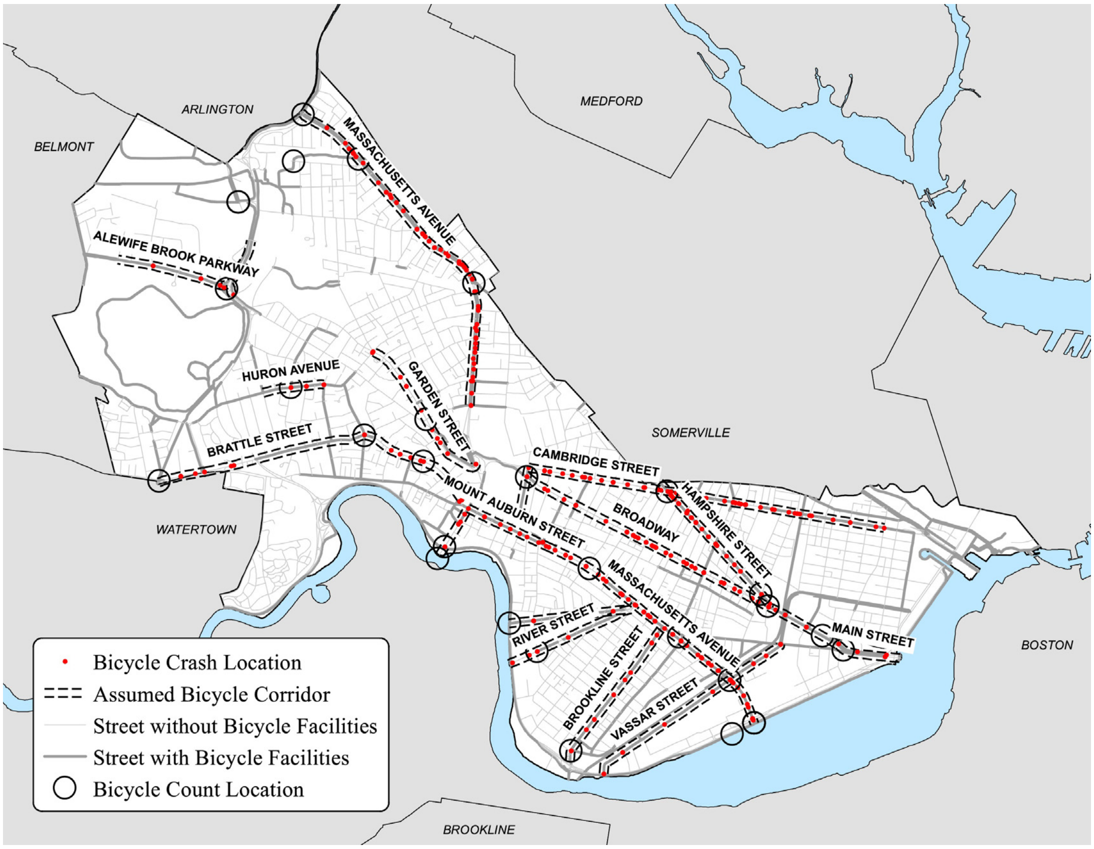
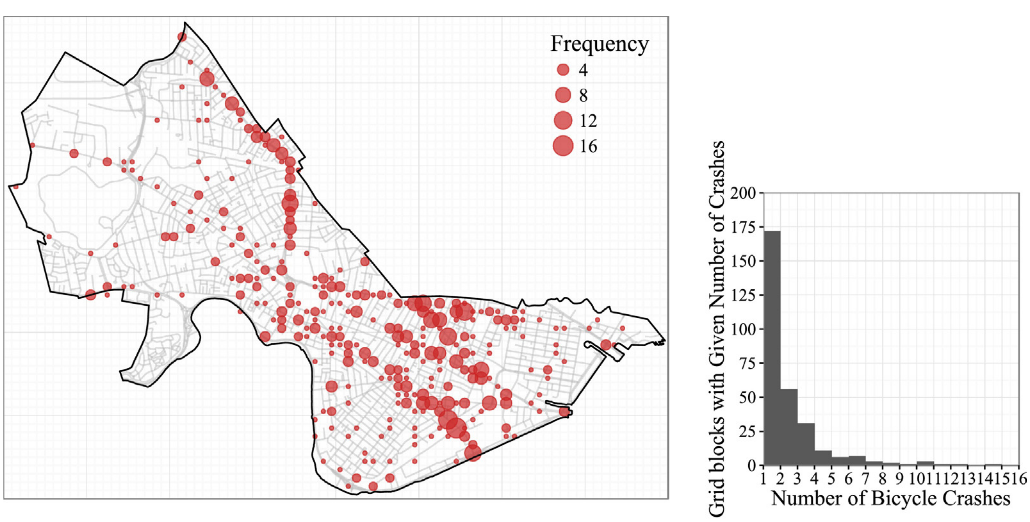


Fig. 3. Map of bicycle corridors, counts, and crashes.

that bicycle volume is simply a smaller proportion of the overall traffic volume. However, comparing bicycle to motorized traffic volume in Fig. 5 clearly shows that there is no correlation between the two. This is largely because bicycles and motorized vehicles have very different factors affecting route choice. Automobiles can be generally assumed to choose the fastest and shortest route depending mainly on distance and road capacity. Meanwhile bicycles are rarely affected by congestion from other cyclists, but instead make choices based on a multitude of safety and comfort factors. Furthermore, motorized traffic operates at a much larger scale of city to city, whereas bicyclists are moving at a scale of block to block. These characteristics result in greatly different proportional flows between the modes that make the two volumes not interchangeable for rate calculation purposes.

Comparing bicycle crash frequency to volume in Fig. 6, there is little that is comparable between *AADT* and *AADB*. It is expected that there will be an increasing relationship between volume and crash frequency. Although there is some level of crashes increasing with *AADB* and *AADT*, it is difficult to develop a definitive conclusion from this limited data.



(a) Crash frequency map (b) Crash frequency distribution

Fig. 4. Crash frequency distribution for Cambridge, MA from 2011–2014.

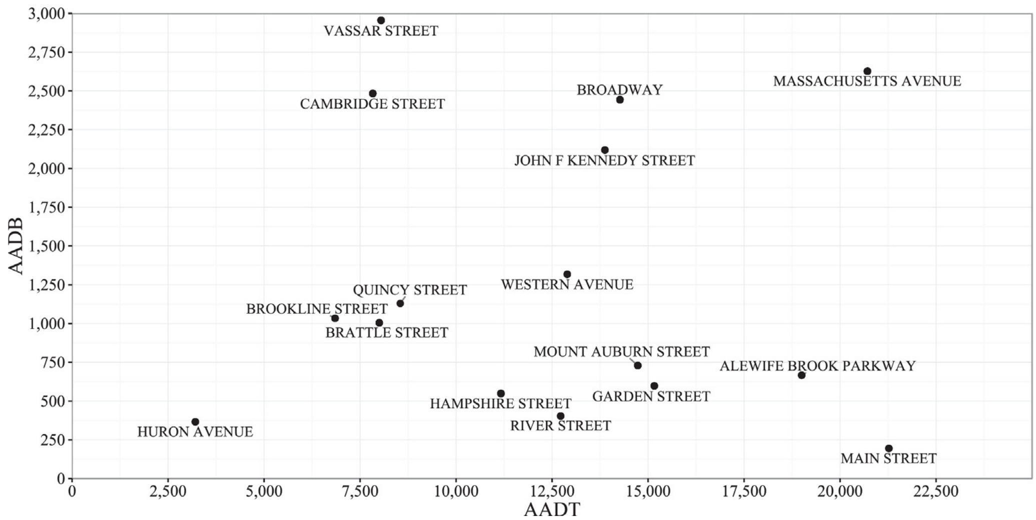


Fig. 5. AADB versus AADT.

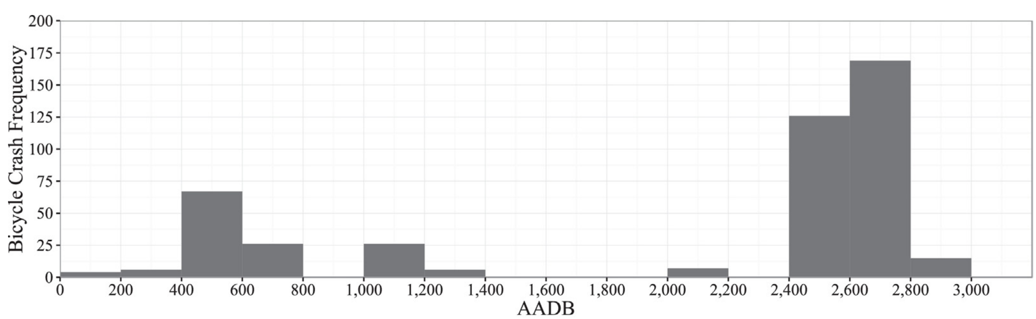
3.3. Crash rates

Crash rates were initially calculated using both the typical rate Eq. (1), and the proposed Eq. (2) for all intersections and mid-block segments. The results of both equations were then plotted against *AADT* and *AADB* for comparison in Fig. 7. The typical crash rate equation results are shown in Fig. 7(a) and proposed crash rate equation results are shown in Fig. 7(b). Although the proposed crash rate equation normalizes using both *AADT* and *AADB* simultaneously, the rates are plotted for both volumes independently for evaluation purposes. In both figures, the points that are plotted based on *AADB* are shown in blue and rates that are plotted based on *AADT* are shown in red.

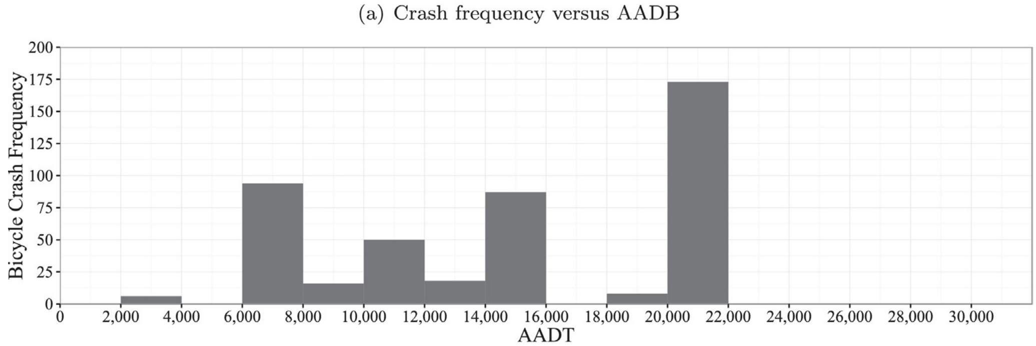
At initial inspection, Fig. 7(a) shows how bicycle-vehicle crash rates are highly non-linear and extremely biased depending on which volume was used to normalize the crash frequency using the typical equation. Meaning that normalizing using only *AADT* tends to overwhelm the relatively low frequency bicycle crashes, resulting in unrepresentative low crash rate. At the same time normalizing using only *AADB* tends to exaggerate crash locations with ultra low bicycle volumes.

Comparing these results with the proposed crash rate calculations shown in Fig. 7(b), we can see that the crash rates are far less biased. There does appear to be some level of non-linearity noticeable, but the relationship appears to be more systematic. Crash rates at locations that were once drowned out by the far greater volume of vehicles are now clearly visible, for example as shown by the Brookline & Granite crash location indicated across Fig. 7(a) and (b).

Plotting these combined crash rates onto the Cambridge grid in Fig. 8(b), it is clear that these corridors are not as dangerous as they might appear in Fig. 8(a). However, other areas of particularly high crash rates, but low volume are visible.

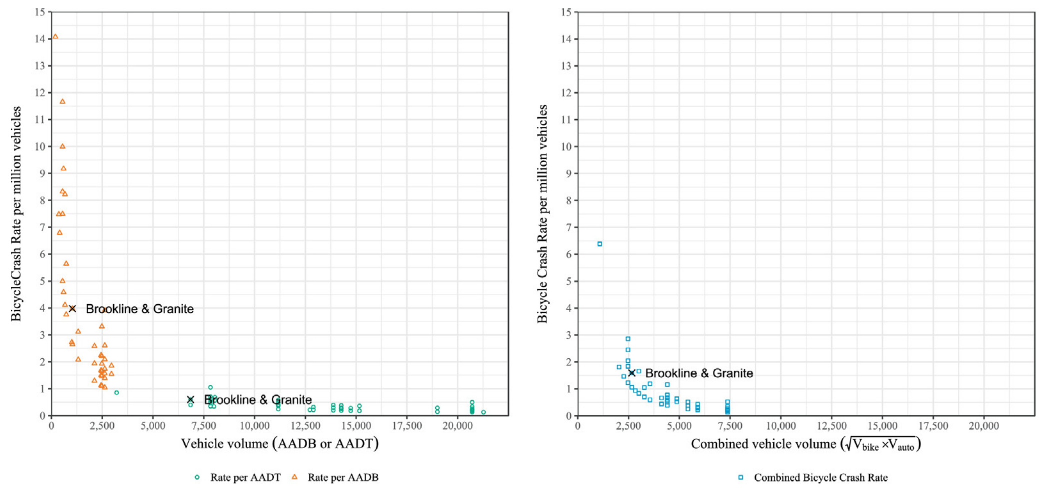


(a) Crash frequency versus AADB



(b) Crash frequency versus AADT

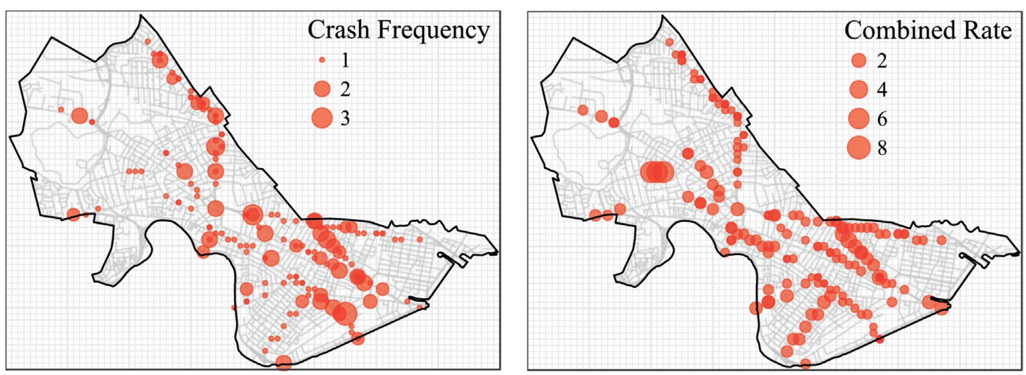
Fig. 6. Crash frequency versus volume distribution.



(a) Typical crash rates versus AADT and AADB

(b) Proposed crash rate versus AADT and AADB

Fig. 7. Crash rate comparison. (For interpretation of the references to color in the text, the reader is referred to the web version of this article.)



(a) Crash frequencies along corridors

(b) Crash rates along corridors

Fig. 8. Crash rate and frequency comparison map for intersections in Cambridge, MA.

4. Conclusions

Bicycles are unique in that they are a mode of their own, yet share the same travel lanes as automobiles. Bicycle crash frequency is affected by not only the bicycle traffic volume itself, but by automobile traffic volume as well. For this reason it is inappropriate to utilize one volume alone for normalization. Utilizing only *AADB* would result in exaggerated rates, whereas using only *AADT* would result in disproportionately small rates. This issue is further exaggerated by the limited availability and high variability of bicycle count data. The proposed framework of estimating demand and assigning corridor volumes aims to alleviate this data challenge and allow for the development of a combined rate equation. Overall, the proposed framework addressed many of the data challenges associated with bicycles by utilizing a sinusoidal model of seasonal bicycle demand and expanded this using corridors in a bicycle network. Last, this enables the development a new combined crash rate equation which yielded effective results at normalizing double exposure crash frequencies.

An area of caution for usage of the equation is that low volume roadways below approximately 3000 vehicles per day have been shown to be particularly difficult to model (Polus and Cohen, 2012). This is a concern when nearly all of the bicycle counts used were below 3000 bicycles per day in this study. Further study is necessary to fully determine whether any additional adjustment is necessary to the methodology. In particular, it is important to understand if any relationship exists between the two volumes when calculating a crash rate. For example, the bicycle and vehicle volumes may need to be weighted separately, or have a function relating the two. Weighting the two volumes could help account for the fact that bicycles typically are only a very small percentage of all traffic.

The proposed equation resulted in a more balanced and comparable crash rate, but a concept that requires further study is the relationship between crash frequency and the relative volumes of bicycles and vehicles. While both bicycle and vehicle traffic volumes affect crash frequency, the relationship between crash frequency and each volume is uncertain. For example, bicycle-vehicle crashes would increase with bicycle volume. Similarly, bicycle-vehicle crashes would also increase with vehicle volume, because the opportunities for conflict would also increase. However, it is unlikely that these two crash-volume relationships are equal. This paper takes a first step toward exposing this question, but further study is necessary.

Although the proposed rate equation is a simplified attempt at incorporating both traffic volumes on the road, it is important to address both volumes when performing crash rate calculations. Bicycle safety is often assessed using only one volume, failing to account for an important normalizer, or are performed using overly aggregated regional data. Though it is important to understand the broader context of bicycle safety, it is necessary to be able to investigate what specific factors may affect the broader context.

The proposed crash rate equation aims to make these in depth investigations more feasible.

Acknowledgements

Special thanks to the UMass SAFE data warehouse for providing the crash data. This research was funded in part through a research project awarded to Michael Knodler and Eleni Christofa by the Safety Research Using Simulation (SAFER SIM) University Transportation Center (UTC) at the University of Iowa. Funding for the UTC Program is provided by the Office of Assistant Secretary for Research and Innovation (OST-R) of the United States Department of Transportation (USDOT).

References

Abdel-Aty, M., Pande, A., 2007. Crash data analysis: collective vs. individual crash level approach. J. Saf. Res. 38 (5), 581–587.
Abdel-Aty, M.A., Radwan, A., 2000. Modeling traffic accident occurrence and involvement. Accid. Anal. Prev. 32 (5), 633–642.
American Association of State Highway and Transportation Officials, 2010. Crash modification factors. In: Highway Safety Manual, 1st Ed., Washington, D.C., Ch. 3.5.3.
Avelar, R., Dixon, K.K., Schertz, G., jan 2015. Identifying Low-volume road segments with high frequencies of severe crashes. Transp. Res. Rec.: J. Transp. Res. Board 2472, 162–171.
Cai, Q., Lee, J., Eluru, N., Abdel-Aty, M., 2016. Macro-level pedestrian and bicycle crash analysis: incorporating spatial spillover effects in dual state count models. Accid. Anal. Prev. 93 (August), 14–22.
Chen, P., 2015. Built environment factors in explaining the automobile-involved bicycle crash frequencies: a spatial statistic approach. Saf. Sci. 79, 336–343.
Chin, H.C., Quddus, M.A., 2003. Applying the random effect negative binomial model to examine traffic accident occurrence at signalized intersections. Accid. Anal. Prev. 35 (March(2)), 253–259.
Commonwealth of Massachusetts, 2014. MassGIS Data – Massachusetts Department of Transportation Roads.
El Esawey, M., 2014. Estimation of annual average daily bicycle traffic with adjustment factors. Transp. Res. Rec.: J. Transp. Res. Board 2443 (December), 106–114.
El Esawey, M., Lim, C., Sayed, T., Mosa, A.I., 2013. Development of daily adjustment factors for bicycle traffic. J. Transp. Eng. 139 (July(8)), 859–871.
Federal Highway Administration, 2013. Traffic Monitoring Guide.
FHWA, 2011. Roadway Safety Information Analysis: A Manual for Local Rural Road Owners.
Fournier, N., Christofa Jr., E., Knodler, M.A., 2017. A sinusoidal model for seasonal bicycle demand estimation. Transp. Res. Part D: Transp. Environ. 50, 154–169.
Hamann, C., Peek-Asa, C., 2013. On-road bicycle facilities and bicycle crashes in Iowa, 2007–2010. Accid. Anal. Prev. 56, 103–109.
Hankey, S., Lindsey, G., Wang, X., Borah, J., Hoff, K., Utecht, B., Xu, Z., 2012. Estimating use of non-motorized infrastructure: models of bicycle and pedestrian traffic in Minneapolis, MN. Landsc. Urban Plan. 107 (September(3)), 307–316.
Jiménez-Mejías, E., Martínez-Ruiz, V., Amezcua-Prieto, C., Olmedo-Requena, R., Luna-del Castillo, J.D.D., Lardelli-Claret, P., 2016. Pedestrian- and driver-related factors associated with the risk of causing collisions involving pedestrians in Spain. Accid. Anal. Prev. 92, 211–218.
Johansson, P., 1996. Speed limitation and motorway casualties: a time series count data regression approach. Accid. Anal. Prev. 28 (1), 73–87.
Joshua, S.C., Garber, N.J., 1990. Estimating truck accident rate and involvements using linear and Poisson regression models. Transp. Plan. Technol. 15 (June(1)), 41–58.
Lord, D., Persaud, B., 2000. Accident prediction models with and without trend: application of the generalized estimating equations procedure. Transp. Res. Rec.: J. Transp. Res. Board 1717 (January), 102–108.
Lord, D., Washington, S.P., Ivan, J.N., 2005. Poisson, Poisson-gamma and zero-inflated regression models of motor vehicle crashes: balancing statistical fit and theory. Accid. Anal. Prev. 37 (January(1)), 35–46.
Ma, J., Kockelman, K.M., Damien, P., 2008. A multivariate Poisson-lognormal regression model for prediction of crash counts by severity, using Bayesian methods. Accid. Anal. Prev. 40 (3), 964–975.
Martínez-Ruiz, V., Jiménez-Mejías, E., Amezcua-Prieto, C., Olmedo-Requena, R., Luna-del Castillo, J.D.D., Lardelli-Claret, P., 2015. Contribution of exposure, risk of crash and fatality to explain age- and sex-related differences in traffic-related cyclist mortality rates. Accid. Anal. Prev. 76 (March), 152–158.
MassDOT, 2016. Crash Rate Summary. https://www.massdot.state.ma.us/highway/Departments/TrafficandSafetyEngineering/CrashData/CrashRates.aspx.
Nordback, K., Marshall, W.E., Janson, B.N., Stolz, E., 2013. Estimating annual average daily bicyclists. Transp. Res. Rec.: J. Transp. Res. Board 2339 (-1), 90–97.
Park, J., Abdel-Aty, M., Lee, J., Lee, C., 2015. Developing crash modification functions to assess safety effects of adding bike lanes for urban arterials with different roadway and socio-economic characteristics. Accid. Anal. Prev. 74 (January), 179–191.
Polus, A., Cohen, M., 2012. A new, non-canonical Poisson regression model for the prediction of crashes on low-volume rural roads. IATSS Res. 35 (2), 98–103.
Poulos, R.G., Hatfield, J., Rissel, C., Flack, L.K., Murphy, S., Grzebieta, R., McIntosh, A.S., 2015. An exposure based study of crash and injury rates in a cohort of transport and recreational cyclists in New South Wales, Australia. Accid. Anal. Prev. 78 (May), 29–38.
Qin, X., Ivan, J.N., Ravishanker, N., 2004. Selecting exposure measures in crash rate prediction for two-lane highway segments. Accid. Anal. Prev. 36 (2), 183–191.
Sanders, R.L., 2013a. Dissecting perceived traffic risk as a barrier to adult bicycling. Transp. Res. Rec.: J. Transp. Res. Board 2000 (January), 16p.
Sanders, R.L., 2013b. Examining the Cycle: How Perceived and Actual Bicycling Risk Influence Cycling Frequency, Roadway Design Preferences, and Support for Cycling Among Bay Area Residents.
Wang, H., Vogt, R., Palm, M., 2015. Geospatial analysis of bicycle network 'Level of traffic stress', bicycle mode choice behaviour and bicycle crashes for risk factor identification. Tech. rep. Oregon State University, Corvallis, OR.
Wood, G., 2002. Generalised linear accident models and goodness of fit testing. Accid. Anal. Prev. 34 (4), 417–427.
Wood, G., 2005. Confidence and prediction intervals for generalised linear accident models. Accid. Anal. Prev. 37 (2), 267–273.
Ye, X., Pendyala, R.M., Shankar, V., Konduri, K.C., 2013. A simultaneous equations model of crash frequency by severity level for freeway sections. Accid. Anal. Prev. 57, 140–149.