Accident Analysis and Prevention 108 (2017) 234–244

Contents lists available at ScienceDirect

Accident Analysis and Prevention

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

How bicycle level of traffic stress correlate with reported cyclist accidents injury severities: A geospatial and mixed logit analysis

Chen Chen[a], Jason C. Anderson[a], Haizhong Wang[a,*], Yinhai Wang[b], Rachel Vogt[a], Salvador Hernandez[a]

[a] School of Civil and Construction Engineering, Oregon State University, Corvallis, OR 97331, United States
[b] Department of Civil and Environmental Engineering, University of Washington Seattle, Seattle, WA, United States

ARTICLE INFO

Keywords:
Bicycle level of traffic stress
Bicycle crash severities
Geospatial mapping
Mixed logit model

ABSTRACT

Transportation agencies need efficient methods to determine how to reduce bicycle accidents while promoting cycling activities and prioritizing safety improvement investments. Many studies have used standalone methods, such as level of traffic stress (LTS) and bicycle level of service (BLOS), to better understand bicycle mode share and network connectivity for a region. However, in most cases, other studies rely on crash severity models to explain what variables contribute to the severity of bicycle related crashes. This research uniquely correlates bicycle LTS with reported bicycle crash locations for four cities in New Hampshire through geospatial mapping. LTS measurements and crash locations are compared visually using a GIS framework. Next, a bicycle injury severity model, that incorporates LTS measurements, is created through a mixed logit modeling framework. Results of the visual analysis show some geospatial correlation between higher LTS roads and "Injury" type bicycle crashes. It was determined, statistically, that LTS has an effect on the severity level of bicycle crashes and high LTS can have varying effects on severity outcome. However, it is recommended that further analyses be conducted to better understand the statistical significance and effect of LTS on injury severity. As such, this research will validate the use of LTS as a proxy for safety risk regardless of the recorded bicycle crash history. This research will help identify the clustering patterns of bicycle crashes on high-risk corridors and, therefore, assist with bicycle route planning and policy making. This paper also suggests low-cost countermeasures or treatments that can be implemented to address high-risk areas. Specifically, with the goal of providing safer routes for cyclists, such countermeasures or treatments have the potential to substantially reduce the number of fatalities and severe injuries.

1. Introduction

1.1. Background

As awareness of the health, economic, and environmental benefits of riding a bicycle continues to increase (Simmons et al., 2015), individuals have been increasingly selecting bicycle as their mode of transportation. As a result, bicycle trips have grown from 1.7 billion in 2001 to 4 billion in 2009 (Milne and Melin, 2014; The League of American Bicyclists, 2015). Unfortunately, this increase in bicycle trips is accompanied by an increase in bicycle fatalities (NHTSA, 2014; Wang et al., 2016). Bicyclists, however, suffer a higher risk of severe injuries compared to motor-vehicles (Beck et al., 2007; National Center for Statistics and Analysis, 2017). Therefore, both national and local bicycle fatality trends motivate state departments of transportation (DOT), transportation planning agencies (e.g., MPOs), local governments, city planners, and engineers to identify bicycle crashes as a primary focus area for investing in safety and infrastructure funding (Wang et al., 2016). However, engineers and planners are facing three interrelated challenges when conducting safety or planning analysis for bicyclists: (1) insufficient data regarding bicycle crashes (i.e., due to under-reporting and the low overall frequency of bicycle crashes at any given point on the system), (2) lack of bicycle volume data on a network scale, and (3) the lack of tools to analyze safety improvement and bicycle planning applications (Lowry et al., 2012). Accordingly, transportation agencies need efficient tools that can improve bicycle safety under constraints of limited budgets. One such method includes the level of traffic stress (LTS) criteria proposed by Mekuria et al. (2012), which is primarily used to predict how various facility improvements will impact connectivity. Although this method has become more

* Corresponding author.
E-mail addresses: chenc4@oregonstate.edu (C. Chen), anderjas@oregonstate.edu (J.C. Anderson), Haizhong.Wang@oregonstate.edu (H. Wang), yinhai@uw.edu (Y. Wang), rachel.vogt@lifetime.oregonstate.edu (R. Vogt), sal.hernandez@oregonstate.edu (S. Hernandez).

http://dx.doi.org/10.1016/j.aap.2017.09.001
Received 1 May 2017; Received in revised form 24 July 2017; Accepted 1 September 2017
0001-4575/ Published by Elsevier Ltd.

commonly used by transportation agencies, it has not been adopted exclusively for safety purposes.

In an attempt to fill the three gaps discussed above, by including LTS and other factors, this study utilizes 10 years of bicycle crash data from four cities in New Hampshire (NH). More specifically, this work seeks to analyze bicycle crashes with the goal of providing a safe and accessible transportation network for pedestrians and bicyclists (Coates, 2014). The crash data used in the current study was created by the NH Department of Transportation (NHDOT) Bike & Pedestrian Team and provided by the New Hampshire Bike-Walk Alliance (NHBWA), in which all reported bicycle and pedestrian crashes between 2002 and 2013 are included. The LTS data was obtained from a pilot project done by NHDOT for a proof of concept, although it has not been endorsed by NHDOT or the NH Bicycle & Pedestrian Advisory Committee (NH BPTAC). Now, The Southern New Hampshire Planning Commission (SNHPC) cooperates with NHDOT on classifying road segments by "Level of Traffic Stress" for roads in the City of Manchester (Bike Manchester, 2017).

Although cycling is on the rise, transportation agencies find it difficult to justify bicycle planning and investment due to the lack of sufficient non-motorized data. However, thanks to the dramatic increase of using GPS devices in smart-phones, the popularity of using apps such as STRAVA provides a valuable database for analyzing cyclist behavior and route choice. STRAVA is a smart-phone based application that records athletic activities, including time, route choice, and demographic information of the cyclist or runner (STRAVA, 2017). The Oregon Department of Transportation (ODOT), as the first organization to purchase and use STRAVA Metro data to inform policy and project decision, stated that this easily accessed data illustrates the future of crowdsourcing data (Jonathan Maus, 2014). NHDOT, collaborating with Plymouth State University, invested $55,000 in a new project to enhance active transportation by using STRAVA data and LTS criteria (New Hamphshire Department of Transportation, 2016). STRAVA Metro data has been used in researches and projects, although it has its own bias: (1) only representing a small proportion of total bike users (1–2.5%), (2) heavily representing recreational cyclists rather than commuters, and (3) GIS skill is needed for analysis and solving the double count issue (Monsere et al., 2017; Jonathan Maus, 2014; Jestico et al., 2016). Therefore, it is also urgent to analyze the correlation between STRAVA data and LTS to identify future potentials in regards to STRAVA data.

1.2. Objective of paper

The objective of this paper is to determine the geospatial and statistical relationship between bicycle LTS and bicycle injury severity. As a result, this work seeks to show how LTS models can serve as an alternative method for bicycle safety and planning analysis. There are three specific goals for this work: (1) determine the correlation between high stress levels and high injury severity, (2) determine the correlation between high stress levels and high crash frequencies, (3) determine if stress levels contribute to the severity of crashes, and (4) identify a correlation between crowdsourcing data (STRAVA) and LTS. By using a stress level analysis to aid in predicting where crashes may occur, communities can allocate funds more effectively for infrastructure safety improvements.

1.3. Organization of paper

This paper is organized as follows: Section 2 reviews the literature on LTS and risk factors identified through previous injury severity studies; Section 3 presents a brief summary of the crash data, the limitations, and the four study sites in New Hampshire included in the geospatial and modeling analysis; Section 4 details the geospatial and mixed logit methodologies used to conduct the analysis; GIS-based visual results and modeling results are provided in Section 5; Section 6 discusses the results of the mixed logit analysis, as well as the STRAVA analysis; and, Section 7 concludes the paper with remarks regarding future work.

2. Literature review

2.1. Pros and cons for LTS

Mekuria et al. (2012) developed a criteria that provides consistent and effective measurement on the transportation network: LTS. This criteria, LTS, can be used by city planners and engineers to make more informed decisions. However, the original idea was created by the Geelong Bike Plan Team in 1978 (Harkey et al., 1998; Wang et al., 2016). Traditional observation and survey data are the main approaches used to measure the effectiveness of LTS, where four different classifications of urban bicyclists (from children with low cycling skill to cyclists who can cycle under any condition) are utilized (Wang et al., 2016). In doing so, the LTS system is defined based on resident cycling comfort level rather than skill level. The four levels of LTS, level 1 to level 4, represent comfort level from high to low. LTS 1 is suitable for children, LTS 2 represents the traffic stress that most adults can tolerate, and LTS 3 and LTS 4 represent greater levels of stress.[1]

Variables used to define LTS include posted speed limit, number of lanes, cycling infrastructure improvements, on-street parking, and lane width (Mekuria et al., 2012). Collecting the necessary data, defining LTS based on the collected data, then utilizing LTS is affordable for small jurisdictions; therefore, small jurisdictions can develop maps for bicycle safety and policy evaluation (Wang et al., 2016). Of the variables used for defining LTS, posted speed limit and the number of lanes are crucial in determining subjects' perceptions of service levels (Kirner Providelo and da Penha Sanches, 2011; Kang and Lee, 2012). Traffic condition is significant, as cyclists prefer cycling along residential streets rather than riding on major streets with higher speeds and higher volumes of traffic (Caulfield et al., 2012; Habib et al., 2014). Bicycle infrastructure improvements, such as buffered bike lanes, correlate with higher cycling rates at the household, neighborhood, and municipal level (Dill and McNeil, 2013; Kirner Providelo and da Penha Sanches, 2011; Wang et al., 2016). Since individuals are more willing to take a route with a lower stress level, infrastructure improvements can also determine route choice (Tilahun et al., 2007; Hood et al., 2011; Arentze and Molin, 2013).

While many studies promote the benefits of LTS, some literature doubts the effectiveness of LTS, specifically the variables used to estimate the bicycle mode share and bicycle trips. Using GPS data, some of the latest research on route choice found that traffic volumes are critically important to better understand route choice (Broach et al., 2012).[2] Traffic volume data can be costly for small jurisdictions; however, it can directly represent the route choice of riders (Winters et al., 2011; Li et al., 2012). Traveler awareness of connectivity is just as important as the availability of bicycle connectivity of a network itself (Lundberg and Weber, 2014). Several studies have also included other factors that may have significant influence on bicycle route choice, such as wayfinding (Wierda and Brookhuis, 1991; Campbell and Lyons, 2008), trip difficulty measures (Milakis and Athanasopoulos, 2014), signalization (Kirner Providelo and da Penha Sanches, 2011; Broach et al., 2012; Titze et al., 2008; Sener et al., 2009), built and natural environment variables (Cervero and Duncan, 2003), and accessibility to a variety of activities and transit stations (Wang et al., 2016). Furthermore, being that prioritization of investments is critical to local transportation agencies, Larsen et al. (2013) used GIS for a spatial comparison. This established a bicycle infrastructure investment

[1] For more detail on LTS, the reader is referred to Mekuria et al. (2012), and Dill and McNeil (2013).

[2] When measuring LTS, traffic volumes are generally not included to mitigate the data intensiveness.

framework that contains the variables not included in the LTS system. However, some jurisdictions may not be able to afford the necessary GIS data as an additional investment.

2.2. A review of alternatives

An alternative to LTS is the Bicycle Compatibility Index created by Harkey et al. (1998). This index allows engineers to determine how compatible a roadway is for allowing efficient operation of both bicycles and motor vehicles at the same time. This method was built based on speed, geometric data, and traffic volume. Bicycle Level of Service (BLOS) described in the Highway Capacity Manual is another alternative to LTS. This method is based on ten attributes (including speed, geometric features, and volume) used to generate a numeric score, then translated to a letter grade to represent bicyclist comfort and safety (Lowry et al., 2012; Wang et al., 2016). BLOS can be applied to entire communities and has assisted in determining improvement scenarios in Moscow, Idaho (Lowry et al., 2012). Rybarczyk and Wu (2010) used a multi-criteria evaluation (MCE) analysis with GIS to integrate supply/demand models for bicycling in Milwaukee, Wisconsin. Specifically, Bicycle Level of Traffic Stress (BLTS) was applied to categorize and analyze bicycle supply. The system computes a six-level categorization that downgrades BLTS as the volume of directional traffic and percentage of heavy-vehicles increase. In addition, BLTS is downgraded as road surface conditions decrease (i.e., extreme cracking, potholes, etc.). The authors stated that this combination of MCE with GIS can meet multiple planning objectives with regard to bicyclists (Rybarczyk and Wu, 2010). Lowry et al. (2016) create a new approach to prioritize bicycle enhancement projects based on a new classification of bicycle stress. This new method measures stress by marginal rate of substitution (MRS). MRS is the rate at which a consumer is willing to give up one good to get another. Lowry et al. (2016) input MRS as a parameter, with the number of lanes and posted speed limit, to represent BLTS.

While these approaches may be more effective in predicting outcomes, the LTS framework offers a much less complicated metric by using criteria that cyclists, citizens, and local officials may readily understand. Additionally, data on traffic volumes, the percentage of heavy-vehicles, and road conditions may not be available or feasible to collect for small- to medium-sized jurisdictions.

2.3. Bike crash severity studies

The multinomial logit model and mixed logit model were used by Moore et al. (2011) to reveal the influence of geometric, environmental, driver, and bicyclist characteristics on bicycle injury severity. They found that intersections, horizontal curves with grades, and heavy-duty trucks under the influence of alcohol and drugs increase the bicyclist injury severity. Yan et al. (2011) also applied the multinomial logit model on reported crash data in Beijing. They found that head-on collisions, angled collisions, no street lighting in darkness, roadways with no median, high posted speed limits, heavy-vehicles, and older cyclists are associated with a higher injury severity level.

Researchers have analyzed factors such as the number of traffic lanes adjacent to bicycle traffic (Greibe, 2003; Petritsch et al., 2006), road curvature (Pai, 2011; Eluru et al., 2008; Kim et al., 2007), roadway characteristics (Greibe, 2003; Schepers et al., 2011), and the presence of a bike lane (Vandenbulcke et al., 2014). Wang and Nihan (2004) discovered that for intersection and network movements, hazardous crossings, right hooks, left sneaks, and complicated interactions are potentially dangerous to cyclists. Oh et al. (2008), Abdel-Aty and Keller (2005), Haleem and Abdel-Aty (2010), Dixon et al. (2012) also found that traffic volume, bicycle volume, speed limit, number of bus stops, and shoulder features were significant factors that influence cyclist risk. In addition, bicycle crashes inherently have their own factors that are specific to bicycle crashes. Two of the more impactful factors are bad weather (e.g., fog, snow, or rain) and the lighting of the roadway under dark conditions (Moahn et al., 2006; Pai, 2011; Mountain and Jarrett, 1996; Stone and Broughton, 2003).

Based on the existing literature, bicycle crash severity studies typically include variables related to roadway geometrics and features, traffic volume, weather conditions, land-use, human factors, and temporal characteristics. However, these studies do not include LTS as an independent variable in the severity analysis. Therefore, this gap in literature is filled uniquely by this paper.

3. Data and study site

3.1. Crash and LTS data

The crash data used in this study includes bicycle crashes from the State of New Hampshire between 2002 and 2013. The crash data includes the location of the crash, the roadway alignment, surface condition, lighting and weather condition at the time of the crash, day and time of the crash, traffic control device, and the level of severity based on the KABCO severity scale (killed, incapacitating, non-incapacitating, possible, and no injury).

To ensure each injury severity level had an adequate proportion of crashes,[3] injury severity levels are joined to create three distinct severities; namely, 'Severe Injury' (fatal and incapacitating injuries), 'Minor Injury' (non-incapacitating injuries), and 'No/Possible Injury' (no injury and possible injuries). Crashes that had an 'Unknown' severity were excluded, as assumptions regarding these crashes can lead to inaccurate model estimates and inferences. Of the 627 total crashes, 44 resulted in a severe injury, 405 resulted in a minor injury, and 178 resulted in no/possible injury. In terms of LTS, 14 crashes occurred on a road classified as LTS 1, 113 occurred on a LTS 2 roadway, 180 occurred on a LTS 3 roadway, and 222 occurred on a LTS 4 roadway. Fig. 1 shows the location of each city, the population of each city, and the number of crashes in each city considered for analysis.

The LTS data, as described previously, was obtained through a pilot project completed in 2014 as a proof of concept by the New Hampshire Bicycle & Pedestrian Transportation Advisory Committee. This data includes bike lane presence and width, speed limit, parking presence and width, residential indicator (road is in a residential area), mid-block crossing, the number of right turn lanes, and the bike lane configuration. It should be noted that bike lane and parking data were collected for both the left and right side of the roadway. However, due to the LTS recorded being different for less than 5% of the observations, the right side LTS measurement is used for analysis.

3.2. Data limitations

The data used for the current study has certain limitations that prevent alternate methods of analysis from being successful without further preparing the data. For example, the data consists only of crashes (e.g., no "zero" observations for crashes that did not happen) and to conduct a crash frequency or crash rate analysis the data would need to be disaggregated based on roadway segments. More, the data used for this analysis was filtered to represent only bicycle related crashes. Therefore, inferences from this work can only be made in regard to bicycle related crashes.

A more consequential limitation of the data is the lack of cyclist characteristics. Many studies have found that user characteristics, such as age, if alcohol was involved, and gender, are significant contributing factors to bicycle crashes; however, such variables were not collected and available for the current study. Due to such a limitation, a specific

[3] If the crash proportions are too skewed to a single severity outcome (i.e., greater than 97% of observations are no injury crashes), applying the mixed logit modeling framework will not work due to convergence problems (Anderson and Hernandez, 2017).

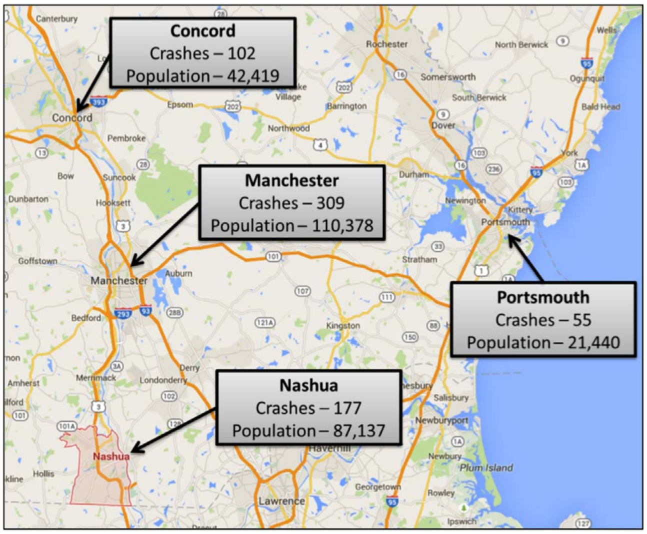

Fig. 1. Four cities from the state of New Hampshire.

modeling framework is applied and will be discussed in detail in the Methodology section. Other notable limitations include the simplicity of the LTS data, the inability to capture bicycle volumes, the irregularity in time intervals between observations, which prevent a time series analysis, and an inherent skewness towards “Injury” crashes as a result of underreporting.

3.3. Descriptive statistics of selected variables

To better understand bicycle crash contributing factors and their corresponding impact on injury severity, a mixed logit modeling framework is implemented. Descriptive statistics of significant variables are shown in Table 1. The dependent variable for this analysis is the maximum recorded injury severity of the cyclist: Severe Injury (fatal and incapacitating), Minor Injury (non-incapacitating), and No/Possible Injury (no injury and possible injury). As formerly discussed, the injury severity levels accounted for 44 (7.02%), 405 (64.59%), and 178 (28.39%) of the observations.

Table 1
Descriptive statistics of significant variables.

Variable description	Mean	Standard deviation
No/possible injury		
Posted speed limit (1 if greater than 30 miles/h, 0 otherwise)	0.104	0.305
Crash location (1 if along roadway, 0 otherwise	0.233	0.423
AADT (1 if between 5000 and 10,000, 0 otherwise)	0.246	0.431
Level of traffic stress (1 if LTS 3, 0 otherwise)	0.287	0.453
Minor injury		
City (1 if Manchester, 0 otherwise	0.477	0.500
Road configuration (1 if divided highway, 0 otherwise)	0.113	0.317
Road geometrics (1 if straight and level, 0 otherwise)	0.774	0.419
Roadway width (1 if 30 feet, 0 otherwise)	0.263	0.440
Traffic control device (1 if traffic signal, 0 otherwise)	0.230	0421
Level of traffic stress (1 if LTS 4, 0 otherwise)	0.354	0.478
Severe injury		
Year crash occurred (1 if before 2005, 0 otherwise)	0.396	0.489
Presence of bike lane (1 if no bike lane, 0 otherwise)	0.834	0.372
Road direction (1 if two-way road, 0 otherwise)	0.633	0.482
Time-of-day (1 if between 9:00 p.m. and 6:00 a.m., 0 otherwise)	0.080	0.271

3.4. STRAVA data

As discussed in Section 1.1, crowdsourced data are more affordable and accessible; therefore, it is vital to assess the potential of using STRAVA data as an alternative or component of LTS. Due to not all data being provided (i.e., the raw STRAVA data), a descriptive analysis is applied to explore the correlation between STRAVA and LTS. The lack of raw data prevented STRAVA from being used as a variable in the modeling process. Identifying such a correlation is the initial step in explaining LTS by crowdsourced data. Total STRAVA trips in 2014, by LTS, in three cities (Concord, Nashua, and Manchester) were provided by NHBWA. The analysis of STRAVA trips, roadway miles, and bicycle-miles-traveled are shown in Section 6.4. This data, purchased by NHDOT, can map out approximately 150,000 rides, each with detailed information regarding the time-of-day, day of the week, season, and local geography along a given segment (Morris, 2014). Since STRAVA data is only provided for each LTS, it is not included as a variable in the presented mixed logit model. Instead, total STRAVA data for each LTS are compared directly with the results of model.

4. Methodology

This section presents the three methodological components for the current study: (1) coding the BLTS network, (2) GIS-mapping of the bicycle crashes to the coded BLTS network, and (3) mixed logit modeling framework used to identify bicyclist injury severity contributing factors.

4.1. Coding LTS network: criteria and procedure

The calculation of LTS was completed in four New Hampshire cities; namely, Concord, Manchester, Nashua, and Portsmouth. Table 2 and the flow chart in Fig. 2 summarize how LTS for each segment is determined. Each city has been sent two feature classes with which to collect data: one for roadway segments and another for intersection approach legs. Domains have been created for most attributes to aid the data collection. There are eleven data attributes collected for roadways and two data items for intersection approach legs. For roadway segments, the data collected include: (1) bike lane presence (right and left), (2) bike lane width (right and left), (3) speed limit, (4) parking presence (right and left), (5) parking width (right and left), (6) residential indicator, and (7) mid-block crossing. The two items for intersection legs include: (1) number of right turn lanes at intersection approach and (2) bike lane configuration at intersection approach.

4.2. GIS-mapping of bicycle crashes

To perform a visual analysis of the crash data and LTS data, both sets of data were imported into ArcGIS. Once in GIS, each layer was modified to show a specific attribute: bicycle crash severity levels for the crash data and LTS measurements for the LTS data. Next, a ‘join’ function was used multiple times to merge the excel formatted crash data (data with the crash information), the geocoded crash data, and

Table 2
Criteria for level of traffic stress in mixed traffic (Mekuria et al., 2012).

Speed limit	Street Width		
	2–3 lanes	4–5 lanes	6+ lanes
Up to 25 miles/h	LTS 1[a] or 2[a]	LTS 3	LTS 4
30 miles/h	LTS 1[a] or 2[a]	LTS 4	LTS 4
35+ miles/h	LTS 4	LTS 4	LTS 4

[a] Use lower value for streets without marked centerlines or classified as residential and with fewer than 3 lanes; use higher value otherwise.

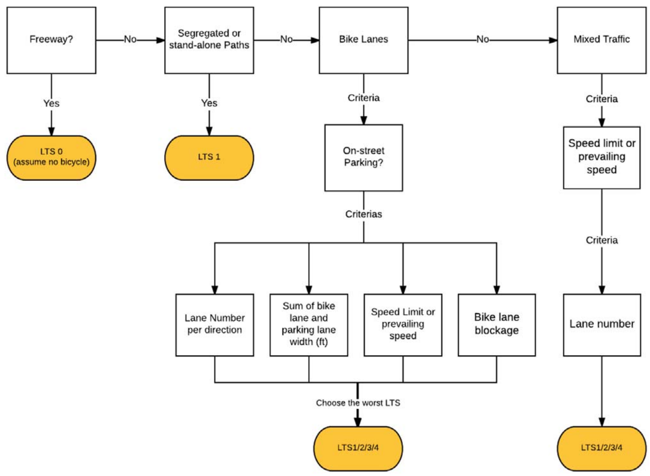

Fig. 2. Flow chart of bicycle level of traffic stress.

the LTS data. As a result, if the crash occurred along a segment with a LTS measurement, the crash now had a corresponding LTS measurement. There were nine cases where a collision occurred on a segment of LTS 0. LTS 0 segments include turnpikes, ramps, private roads, or unknown facilities, and were excluded from further analysis. The final dataset was used for the statistical and visual analysis.

4.3. Mixed logit modeling framework

Crash data, unfortunately, does not contain each and every variable that contributes to a given injury severity (often because such data is not on data collection forms) and can have variation within existing variables. Taking that into consideration, a specific method is chosen to better parameter estimates and provide more accurate inferences, the mixed logit model (see Mannering et al., 2016 for a full discussion of unobserved heterogeneity and its role in transportation safety analyses).

The mixed logit model begins with a linear-in-parameters severity function for each injury severity considered (Washington et al., 2011):

$$S_{\text{in}} = \beta_i X_{\text{in}} + \varepsilon_{\text{in}} \tag{1}$$

where S_{in} is a linear-in-parameters function for bicycle crash n resulting in injury severity i, β_i is a vector of estimable parameters, X_{in} is a vector of explanatory variables (e.g., LTS, roadway characteristics, weather characteristics, etc.), and ε_{in} is the disturbance term that attempts to capture the unobservable factors in the crash data.

Considering Eq. (1), the standard multinomial logit model can now be represented as (Washington et al., 2011; McFadden, 1981):

$$P_n(i) = \frac{e^{\beta_i X_{\text{in}}}}{\sum_{\forall I} e^{\beta_i X_{\text{in}}}} \tag{2}$$

where $P_n(i)$ is the probability that bicycle crash n results in injury severity i and all other terms have been defined previously. However, the disturbance term ε_{in} is unable to capture all of the unobserved factors within the crash data. For instance, if there is parking between a dedicated bicycle lane and the roadway, the parked vehicles are likely to be involved in the crash instead of the cyclist (reducing injury severity). Yet, if the parked vehicle is hit at a high speed and the cyclist is struck, there is likely to be an increase in severity. This is not represented in the crash data, but has the potential to impact injury severity (often referred to as unobserved heterogeneity). Therefore, to account for such factors, Eq. (2) is now written as (Washington et al., 2011):

$$P_n(i|\phi) = \int_x \frac{e^{\beta_i X_{\text{in}}}}{\sum_{\forall I} e^{\beta_i X_{\text{in}}}} f(\beta_i|\phi) d\beta \tag{3}$$

where $P_n(i|\phi)$ is the weighted outcome probability of injury severity i conditional on $f(\beta_i|\phi)$, where $f(\beta_i|\phi)$ is the density function of β with distributional parameter ϕ. Specifically, $f(\beta_i|\phi)$ is what allows parameters to vary based on a distribution of β that is defined by the analyst (this distribution is generally specified to be normally distributed). In other words, β can now account for observation-specific variations of explanatory variables X_{in} on the injury severity outcome probabilities (Washington et al., 2011).

To make inference regarding the impact of significant factors from model estimates, marginal effects are computed to determine the effect of indicator variable X_{ink} on the outcome probability of injury severity i (Greene, 2012):

$$M_{X_{\text{ink}}}^{P_n(i)} = P_n(i)[\text{given } X_{\text{ink}} = 1] - P_n(i)[\text{given } X_{\text{ink}} = 0] \tag{4}$$

where $M_{X_{\text{ink}}}^{P_n(i)}$ is the effect of indicator variable X_{ink} on the outcome probability of injury severity i when X_{ink} changes from zero to one and all other variables remain constant (equal to their means).

The final step in the modeling process is to determine the significance of the log-likelihood values, where this is done through a log-likelihood ratio test (Washington et al., 2011):

$$\chi^2 = -2[\text{LL}(\beta_{\text{Fixed}}) - \text{LL}(\beta_{\text{Random}})] \tag{5}$$

where $LL(\beta_{Fixed})$ is the log-likelihood at convergence for the model with fixed parameters (sign of parameter β does not vary across observations), $LL(\beta_{Random})$ is the log-likelihood at convergence for the model with random parameters (sign of estimated random parameters does vary across observations), and χ^2 is a chi-square statistic with degrees of freedom equal to the number of estimated random parameters in $LL(\beta_{Random})$.

5. Geospatial mapping and modeling results

5.1. GIS-based mapping results

In addition to the basic relationships stated previously, the maps generated using ArcGIS provide further insight into potential patterns and a geospatial relationship between LTS measurements and crash severity. Fig. 3 shows the central area of Concord. One can observe that the majority of "Injury" type collisions occurred on three or four specific roads that were classified as LTS 3 or LTS 4, where the majority of severe injury crashes occurred on roads with LTS 4. Several roadway segments classified as LTS 3 or LTS 4 have no reported crashes, which is likely due to the low frequency of bicycle trips taken on these routes.

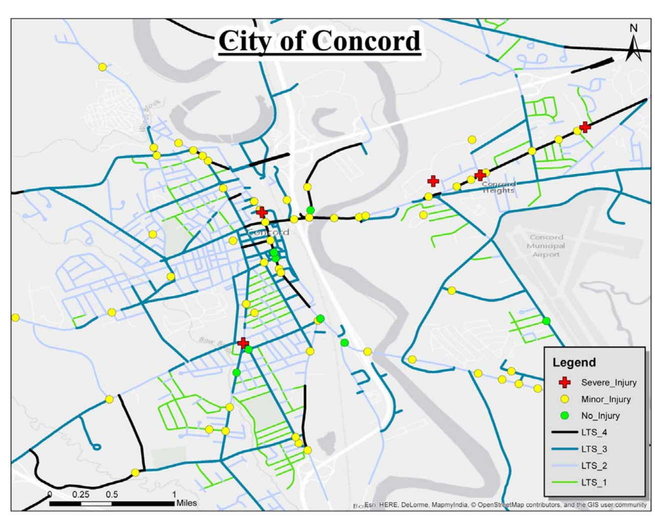

Fig. 3. City of Concord.

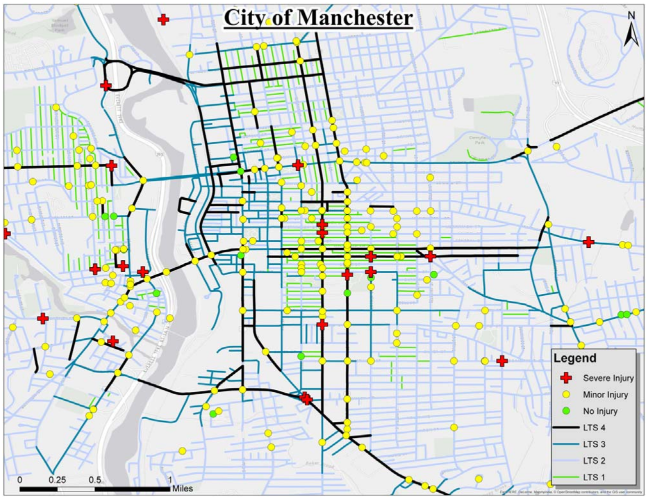

Fig. 4. City of Manchester.

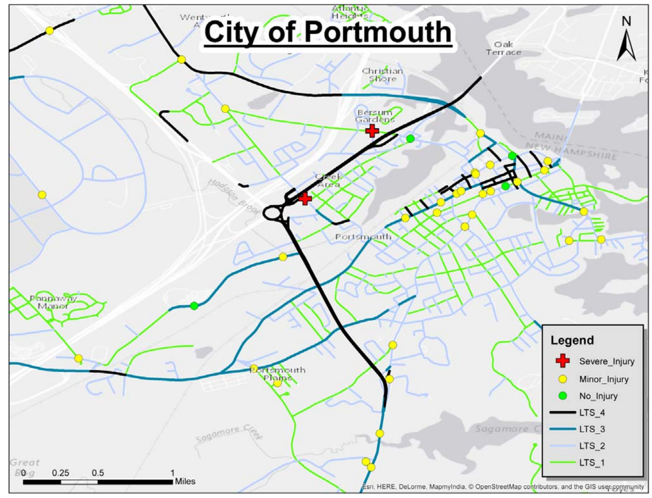

Fig. 6. City of Portsmouth.

Fig. 4 shows the central area of Manchester. Tantamount to Concord, the majority of "Injury" type crashes occurred on roadways that were classified as LTS 3 or LTS 4, while the majority of severe injury crashes occurred on roadways with LTS 4.

Fig. 5 shows the city of Nashua. Once more, the majority of "Injury" type crashes are along roadways with LTS 3 or LTS 4. The majority of crashes took place in downtown Nashua, right near the junction of HWY-111 and HWY-101A crossing Merrimack River. The roadway segments here are predominantly two-way, two to four lanes, and have an approximate AADT of 21,000. Most of the road segments have a speed limit of 30 miles/h and are non-residential roads. Further, these roadways do not have a dedicated bike lane or motor-vehicle parking. The two reported fatalities occurred on LTS 4 segments.

Fig. 6 shows Portsmouth. In this city, it is difficult to distinguish a clear relationship between LTS and crash severity due to the low number of reported crashes. The majority of crashes took place on LTS 3 and LTS 4 segments in downtown Portsmouth, or along HWY-1/Lafayette Rd. with LTS 3.

5.2. Mixed logit model

A total of 14 variables were found to be statistically significant in determining the outcome probability of the three injury severities considered; best fit model specifications and marginal effects are shown in Table 3. From Eq. (5), χ^2 is equal to 62.4 with 4 degrees of freedom (the number of estimated random parameters). Based on a chi-square distribution, these results indicate that the mixed logit log-likelihood is of more significance than the log-likelihood using fixed parameters (all variables are assumed to be homogeneous across observations) with well over 99% confidence.

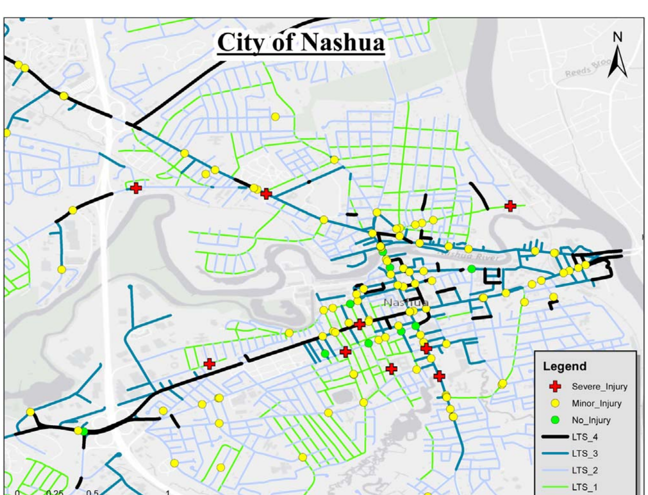

Fig. 5. City of Nashua.

To discuss model results, each severity will be discussed separately in Section 6.

6. Discussion of mixed logit model

6.1. Severe injury

Table 3 shows that four factors are found to contribute to the outcome probability of sustaining a severe injury, with just one of the four factors being heterogeneous across crash observations. In particular, the estimated parameter for crashes that occurred before the year 2005 is found to be random and normally distributed. With a mean of 0.11 and standard deviation of 1.37, the normal curve suggests that the estimated parameter mean is less than zero for 46.8% of bicycle crashes and greater than zero for 53.2%. That is, bicycle crashes that happened before 2005 are less likely to result in a severe injury for 46.8% of cyclists, but more likely for 53.2%. In addition, this variable has a considerable impact on severe injury outcomes, as there is a 0.030 higher probability of sustaining a severe injury if the crash occurred before 2005.[4] This estimated parameter may be attempting to capture cyclist behavior and the variation in bicycle facilities before and after 2005. For instance, the increase of bicyclists in the U.S., heightened attention towards health, economical impacts, and environmental benefits of bicycling have resulted in an increased emphasis in regard to bicycle safety and bicycle facilities since 2005 (Simmons et al., 2015; Milne and Melin, 2014; The League of American Bicyclists, 2015). Specifically, the emphasis in bicycle safety and bicycle facilities has dramatically increased the number of bicycle safety infrastructure projects or programs (1077 in 2005 to 2424 in 2009 nationwide) in most states across the U.S. (Twaddell et al., 2016). This finding in New Hampshire is consistent with the general trend in the U.S., in which bicyclist fatalities decreased by 13% from 1990 to 2013 (Twaddell et al., 2016). At the same time, the increase in the number of bicycle trips in the U.S. (1.7 billion in 2001 to 4 billion in 2009 The League of

[4] The year 2005 was chosen as the threshold for the statistical analysis based on the general trend in the number of bicyclists, infrastructure changes, and bicycle crash fatalities from 1990 to 2010.

Table 3
Best fit mixed logit results and marginal effects.

Variable			Marginal effects		
	Coefficient	*t*-Statistic	No injury	Minor injury	Severe injury
No/possible injury					
Constant	−1.12	−3.99			
Posted speed limit (1 if greater than 30 miles/h, 0 otherwise)	0.70	1.78	0.012	−0.011	−0.001
Crash location (1 if along roadway, 0 otherwise	0.48	1.85	0.020	−0.017	−0.002
AADT (1 if between 5000 and 10,000, 0 otherwise)	−0.80	−1.85	−0.008	0.005	0.003
(Standard deviation of normally distributed parameter)	*(1.43)*	*(2.13)*			
Level of traffic stress (1 if LTS 3, 0 otherwise)	0.52	2.03	0.026	−0.023	−0.003
Minor injury					
City (1 if Manchester, 0 otherwise	−0.38	−1.71	0.165	−0.172	0.006
Road configuration (1 if divided highway, 0 otherwise)	−0.97	−2.83	0.017	−0.021	0.004
Road geometrics (1 if straight and level, 0 otherwise)	0.56	2.23	−0.058	0.072	−0.014
Roadway width (1 if 30 feet, 0 otherwise)	−0.13	−0.33	0.016	−0.020	0.004
(Standard deviation of normally distributed parameter)	*(2.42)*	*(2.77)*			
Traffic control device (1 if traffic signal, 0 otherwise)	0.36	1.32	−0.010	0.013	−0.003
Level of traffic stress (1 if LTS 4, 0 otherwise)	−0.20	−0.67	0.019	−0.022	0.004
(Standard deviation of normally distributed parameter)	*(1.09)*	*(1.83)*			
Severe injury					
Constant	−1.89	−4.32			
Year crash occurred (1 if before 2005, 0 otherwise)	0.11	0.20	−0.010	−0.019	0.030
(Standard deviation of normally distributed parameter)	*(1.37)*	*(2.42)*			
Presence of bike lane (1 if no bike lane, 0 otherwise)	−2.03	−4.23	0.031	0.044	−0.075
Road direction (1 if two-way road, 0 otherwise)	1.08	2.38	−0.015	−0.024	0.039
Time-of-day (1 if between 9:00 p.m. and 6:00 a.m., 0 otherwise)	1.07	2.02	−0.003	−0.005	0.008
Model statistics					
Number of observations	627				
Log-likelihood at zero	−518.04				
Log-likelihood at convergence	−486.84				
McFadden pseudo R^2	0.06				

American Bicyclists, 2015) may encourage cautious driving in urban areas where more bicyclists are expected on the roadway; this could be understood as “Safety in Number.”

Bicycle crashes that occurred where a bike lane was not present decreases the likelihood of sustaining a severe injury. According to marginal effects, no bicycle lane decreases the probability of a severe injury by 0.075, on average. This finding appears to violate the common understandings of bicycle safety; however, it is logical when considering where bike lane facilities may be located. That is to say, bike lanes are often present on higher functional classifications, such as urban arterials and collectors with higher traffic speeds and volumes. With that in mind, high speed can be a primary contributing factor to more severe injuries. For example, the right-of-way for the dedicated bike lane may cause drivers to pay less attention to bicyclists and/or have the potential to cause drivers to travel at faster speeds (i.e., drivers are likely to believe driving faster is safe if the bike lane is isolated). While it is common perception that bike lanes become a protective measure used on major roadways, they have been found to be associated with a higher crash frequency (they may not be associated with a higher crash rate depending on the length of the roadway segment) (Wei and Lovegrove, 2013; Dolatsara, 2014). Bike lanes, to some degree, can attract more bicyclists while also putting them in the proximity of dangerous traffic conditions. On the contrary, most local roads do not have bicycle lanes and results in bicyclists sharing the right-of-way with motor-vehicles. In these cases, being that the roadway is shared, it can lead to motorists driving more cautiously and aware.

Bicycle crashes that happened on two-way roads are found to significantly impact severe injury outcomes and are homogeneous across observations. Based on marginal effects, bicycle crashes that occurred on two-way roads have a 0.039 increase in probability of resulting in a severe injury. This finding suggests that roadways with two-way traffic, in the four cities analyzed, are more dangerous than one-way roadways (in terms of severe injury crashes). If cyclists are traveling on the wrong side of the roadway, this may be attributed to the opposite flow of traffic (i.e., against traffic). Crashes that occurred between 9:00 p.m. and 6:00 a.m. are more likely to result in a severe injury and, based on marginal effects, have a 0.008 higher probability of a severe injury. While crashes that took place in the dark were more likely to result in severe injuries, the effect is relatively small when compared to the other significant severe injury factors. Other studies have also found that crashes in dark conditions are more likely to result in severe injuries (Eluru et al., 2008). Being that this variable reflects the lighting condition on roadways in New Hampshire, this result suggests that transportation agencies identify roadways with inefficient lighting and increase visibility for bicyclists riding during overnight hours.

6.2. Minor injury

Referring to Table 3, two estimated parameters are found to be heterogeneous for minor injury outcomes; namely, crashes that occurred on a 30 feet wide roadway and crashes that occurred on roadway segments with LTS 4. The remaining estimated parameters (crashes that happened in Manchester, divided highways, straight and level roadways, and traffic signals) in the minor injury severity function are homogeneous, as the estimated standard deviations of the parameters are not significantly different from zero.

With regard to LTS, LTS 4 has a random and normally distributed parameter with a mean of −0.20 and a standard deviation of 1.09. This result suggests that 42.7% of bicycle crashes that happened under LTS 4 are more likely to result in a minor injury, while 57.3% are less likely to result in a minor injury. Further, marginal effects show a 0.022 lower probability, on average, of sustaining a minor injury if the crash occurred on a roadway with LTS 4. The heterogeneous nature may stem from different cyclist skill levels or the level of caution exhibited by bicyclists riding on LTS 4 roadways. For instance, high skilled bicyclists may be able to avoid a more serious injury, as are bicyclists riding with extreme caution and awareness due to higher LTS. Intuitively, if a factor is found to increase or decrease the likelihood of a severe injury, it is assumed to have the opposite effect on the likelihood of no injury. However, according to marginal effects, this work finds that LTS 4 increases the probability of both no injury and severe injury, albeit marginally for severe injuries at 0.004. LTS 4 represents high stress and low comfort for cyclists; therefore, these counterintuitive findings can prompt an investigation into the criteria used for defining LTS 4. Being that LTS 4 is typically assigned to roadways with high posted speed limits, bicyclists are more likely to suffer a severe injury if involved in a crash with a motor-vehicle traveling at a high speed. Another potential reason might stem from higher heavy-vehicle volumes on major roadways with high posted speed limits or more lanes. Due to the larger mass of heavy-vehicles, previous work has shown that bicycle crashes with heavy-vehicles are more likely to cause severe injuries when compared to crashes with passenger vehicles (Benepe et al., 2005; Moore et al., 2011; Gelino et al., 2012). On the other hand, if a cyclist collides with a fixed-object as opposed to a moving vehicle, less severe injuries may be expected.

The estimated parameter for crashes that happened on a 30 feet wide roadway is found to be random and normally distributed with a mean of −0.13 and a standard deviation of 2.42.[5] This suggests that for 47.9% of bicycle crashes on roadways with a width of 30 feet are more likely to result in a minor injury and less likely for the remaining 52.1%. In terms of impact, marginal effects show a 0.02 decrease in minor injury probability for crashes that occurred on 30 feet wide roadways. This random parameter may be attempting to capture the differences in road configurations, such as 30 feet wide roadways with three lanes or 30 feet wide roadways with two lanes. In particular, previous work has shown that roadways with narrow lane widths and high posted speed limits are associated with more severe injuries (Federal Highway Administration, 2003).

The remaining significant factors, as described previously, are homogeneous and decrease the likelihood of a minor injury. The factor with the largest impact are crashes that occurred in Manchester, as marginal effects show a 0.165 increase in no injury probability and a 0.172 decrease in minor injury probability. A possible explanation for no injury crashes being more likely may be linked to the long history of biking, bicycle infrastructure, and pedestrian infrastructure in Manchester (Robidoux, 2017). Straight and level roadways increase the probability of a minor injury crash by 0.072, according to marginal effects, while decreasing the likelihood of no/possible injury and severe injury. The increase in minor injury likelihood on straight and level roadways may be a result of motor-vehicle drivers paying less attention to their surroundings, or being distracted. For example, straight and level roadway segments are prone to better visibility and do not require the driver to turn; therefore, creating a sense of security for the driver. However, this relaxed state can cause drivers to incidentally swerve or sway onto the shoulder, where impact with a cyclist would likely result in an injury. With regard to traffic control devices, crashes where a traffic signal is present have a 0.013 higher probability of resulting in a minor injury based on marginal effects. Traffic control, in general, has been found to have unstable impact on severity (Wei and Lovegrove, 2013; Chen, 2015; Carter et al., 2006).

6.3. No/possible injury

Regarding no/possible injury severity outcomes, crashes where AADT is between 5000 and 10,000 is found to be heterogeneous across crash observations. The remaining three parameters (crashes with a posted speed limit greater than 30 miles/h, crashes along the roadway, and LTS 3) are found to be homogeneous across crash observations, as the estimated standard deviations of the parameters are not significantly different from zero.

Regarding AADT between 5000 and 10,000, the estimated parameter is found to vary across observations (following a normal distribution) with a mean of −0.80 and a standard deviation of 1.43. This indicates that AADT between 5000 and 10,000 increases the likelihood of no/possible injury for 28.8% of bicycle crashes, yet decreases the likelihood of no/possible injury for the remaining 71.2%. Marginal effects suggest that AADT from 5000 to 10,000 decreases the probability of no/possibly injury, on average, by 0.008, but increases the probability of sustaining minor and severe injuries by 0.005 and 0.003, respectively. As is shown, AADT between 5000 and 10,000 has a small-scale impact on no/possible injury. However, this finding still suggests that bicyclists have a higher likelihood of sustaining a more severe injury when AADT is between 5000 and 10,000. This is likely related to traffic operations, speed, and driver behavior. For example, streets with AADT between 5000 and 10,000 are typically higher classifications (e.g., arterials and collectors) where posted speed limits are higher. As a result, it is likely that the cyclists sustain an injury if a crash occurs. The variation, however, may be associated with congested conditions where speeds are much lower. More, the variation might be explained by the cyclist's level of awareness when riding on routes with higher traffic volumes.

In regards to LTS, LTS 3 increases the likelihood of a no/possible injury crash. Specifically, there is a 0.026 higher probability of sustaining no/possible injury if a crash happens on a roadway with LTS 3. This interesting finding suggests that cyclists are safer biking on roadways with LTS 3, in terms of injury severity. This finding may be associated with bicyclists exhibiting more caution when riding on a LTS 3 roadway (LTS 3 roadways are often urban arterials or major collectors, as defined by Lowry et al., 2012). This phenomenon remains consistent with the estimates of LTS 4, in which LTS 4 increases the likelihood of no/possible injury (marginal effect of 0.019 for no/possible injury). However, while LTS 4 also slightly increases the probability of sustaining a severe injury, according to marginal effects, LTS 3 slightly decreases severe injury probability. This is likely explained by the speed at which crashes occur on LTS 4 roadways when compared to LTS 3 roadways.

Crashes along the roadway increase the likelihood of no/possible injury. To quantify, based on marginal effects, there is a 0.020 higher probability of no/possible injury for crashes along the roadway. This finding may be explained by crashes that happen in downtown urban areas where speeds are low and drivers are more aware of bicycles. Posted speed limits greater than 30 miles/h result in a 0.012 higher probability of sustaining no/possible injury based on marginal effects, but at a relatively smaller magnitude than other significant variables. Due to other researchers finding that higher speeds are correlated with more severe injuries (Eluru et al., 2008; Kim et al., 2007; Yan et al., 2011), this finding may be data-specific. As such, further investigation into the effect of posted speed limits on bicycle injury severity in New Hampshire may be required. However, this finding may be a result of the underreporting issue in New Hampshire, where only property damage in excess of $1000 is required to be reported. Previous studies have also found that underreporting is an influential issue, especially for pedestrian and bicycle crash data (Agran et al., 1990; Stutts et al., 1990). Another possible reason may be linked to the advanced bicycle facilities installed along major roadways with high posted speed limits in New Hampshire. Therefore, providing protection has the potential to mitigate crash severity if a crash occurs (Robidoux, 2017).

6.4. STRAVA data analysis

As discussed in 3.4, a descriptive STRAVA analysis is applied to explore the correlation between STRAVA and LTS. Shown in Table 5,

[5] Variables for widths greater than or equal to 30 feet and greater than 30 feet were tested and not found to be statistically significant (i.e., *t*-statistics approximately zero). This was also true for widths less than 30 feet. Therefore, to explore the impact of roadway width, several widths were tested. In the end, the only width to have statistical significance was a width equal to 30 feet.

Table 4
LTS 3 and LTS 4 Impact (▲ represents an increase in probability and ▼ represents a decrease in probability).

LTS	No/possible injury	Minor injury	Severe injury
3	▲	▼	▼
4	▲	▼	▲

Table 5
STRAVA data by LTS in Concord, Nashua, and Manchester, NH.

City	LTS	Total STRAVA trips	Roadway miles	BMT
Concord	0	19,811	165	3972
	1	9764	34	818
	2	68,088	68	7302
	3	104,913	76	11,673
	4	70,052	108	27,891
Nashua	0	22,339	129	2,889,522
	1	43,841	65	2,830,179
	2	175,747	194	34,070,217
	3	83,711	32	2,687,017
	4	37,675	17	623,510
Manchester	0	1401	21	29,811
	1	147,473	299	44,100,066
	2	77,832	54	4,179,711
	3	37,994	27	1,032,501
	4	5600	51	287,485
	99*	2767	22	61,667
Total	0	43,551	315	2,923,305
	1	201,078	398	46,931,063
	2	321,667	316	38,257,230
	3	226,618	135	27,914,891
	4	113,327	176	938,886

BMT: bicycle-miles-traveled.
99*: private roads in the STRAVA data that are not in the LTS study.
0: turnpikes, ramps, private roads, or unknown facilities.

the majority of STRAVA trips are accruing on lower LTS roadways. Of the most traveled roadways, LTS 2 has the most total STRAVA trips and LTS 4 has the least total STRAVA trips (only LTS 1 to LTS 4 are compared, as LTS 0 represents freeways where bicycles are prohibited). Although the STRAVA data heavily represents recreational trips, cyclists using STRAVA choose similar routes as commuter bicyclists Jestico et al. (2016). Hence, this distribution suggests that LTS criteria can capture the route choice of bicyclists in urban areas of New Hampshire. This is also applicable due to bicyclists naturally choosing routes with lower levels of stress.

By comparing the total STRAVA trips and injury severity on LTS 4 and LTS 3 roadways (shown in Table 4), LTS 4 increases the likelihood of sustaining a severe injury according to model estimations and has fewer total STRAVA trips. In other words, the larger number of bicyclists, the safer the route in terms of injury severity. Previous works have found similar results, but focus more on crash rate than crash severity (Jacobsen, 2003; Nordback et al., 2014). Additionally, total STRAVA trips for each LTS in the three cities are slightly different. Concord has more bicycle trips on LTS 3, Nashua has more on LTS 2, and Manchester has more on LTS 1. This phenomenon may be a result of the differences in demographic characteristics, bicyclist behaviors, and infrastructure between the three cities.

7. Conclusion and policy recommendation

Using 10 years of crash data in four New Hampshire cities, the current study examined the relationship between LTS and cyclist injury severity. A mixed logit modeling framework and maps created in ArcGIS were used to assess this relationship. LTS, as a relatively new evaluation criteria and used by some transportation agencies (i.e., ODOT and NHDOT), was chosen due to its simplicity in terms of acquisition. Such simplicity makes it an ideal criteria for smaller communities that have limited finances. This methodology can be used as a proxy for future crash risk assessment, regardless of the presence of historical crash data. Following are conclusions and policy recommendations identified through this work.

7.1. LTS

Results from the mixed logit model suggest that LTS can be a useful tool in predicting crash severity. More, LTS can serve as a viable tool used by transportation agencies, planners, and engineers to prioritize infrastructure investments. Findings, recommendations, and specific limitations include:

- Crashes on roadways with LTS 3 are less likely to result in a severe injury when compared to crashes on roadways with LTS 4.
- Agencies can consider redesigning/improving, or removing, bicycle facilities on roadways with LTS 4. Bicycle facilities inherently attract cyclists, and for LTS 4 roadways, can put cyclists in a dangerous situation where a severe injury crash is more likely. Verma et al. (2016) and Handy et al. (2010) indirectly justify this recommendation by concluding that a negative bicycling environment has a negative impact, even when proper bicycling infrastructure is provided.
- Being that safety and comfort are critical for encouraging car commuters to shift to bicycle commuting (Muñoz et al., 2016), roadways with lower LTS can be used to promote the idea of active transportation.
- Target residents that do not own a car (possibly a lower income group) to encourage them to ride on lower LTS roadways, as safety and comfort level are not major barriers (Muñoz et al., 2016).
- LTS 1 and LTS 2 are not statistically significant injury severity factors; therefore, agencies can consider revising LTS criteria or re-evaluating the data collection process for LTS.

Thus, it can be concluded that LTS provides some insight into where bicycle collisions may occur. In addition, LTS can be a viable option for agencies to consider when looking at bicycle safety models; this is especially true when no other analysis has been done and limited resources are available. Safety models and visual maps provide insight into potentially dangerous corridors or roadway segments, and can serve as evidence for future policy and investment recommendations.

7.2. STRAVA

STRAVA data was provided for each LTS rather than for each roadway segment; hence, the STRAVA data was compared directly with LTS and not included in the modeling process. However, some useful conclusions and recommendations can be inferred:

- LTS has the potential to capture route choice of bicyclists and can be used to estimate ridership.
- Bicyclists tend to choose bicycle routes with lower LTS.
- Total STRAVA data for each LTS in each city are slightly different. This suggests that jurisdictions may want to consider building their own evaluation process for using LTS to estimate ridership; or, partner to establish a standard for collecting and evaluating LTS data.

Both estimated ridership and estimated risk can be used to influence project selection, prioritize between projects, and/or influence safety program priorities. This method can be implemented on an entire city network or a sub-area of a large city network where bicycles have access.

7.3. Other factors

Modeling results suggest that darkness (crashes that occurred between 9:00 p.m. and 6:00 a.m.), two-way direction roadways, crashes that happened before the year 2005, straight and level roadway segments, and crashes where a traffic signal was present increase the likelihood of sustaining a minor or severe injury if a crash occurs. The presence of a bike lane, roadways that are 30 feet wide, divided highways, crashes that occurred in Manchester, and crashes that happened along the roadway decrease the likelihood of a severe or minor injury, or increase the likelihood of no/possible injury. In addition, posted speed limits greater than 30 miles/h increases the likelihood of sustaining no/possible, but further investigation is recommended to better understand the effect of posted speed limits on bicycle injury severity in New Hampshire. More details and further explanation can be found in the Discussion section. The following are key recommendations based on analysis results:

- The finding in regard to two-way/one-way direction roadways suggests that city planners consider building more bicycle facilities on one-way roadways to decrease the likelihood of more severe crashes.
- The influence of darkness suggests that street lighting investments can be a practical and economically viable solution to improve bicycle safety.
- Being that the presence of bike lanes can increase bicycle usage (Verma et al., 2016), but no bike lane was found to decrease the likelihood of a severe injury in the present research, transportation agencies in New Hampshire can investigate the influence of bike lanes on bicycle safety. This may include identifying locations where the presence of bike lanes can improve safety, assessing improvements to existing bicycle facilities and their impact on safety, or determining the effect of no bike lanes and why there is the potential to reduce the likelihood of severe injuries.
- Crashes that happened in Manchester were more likely to result in no/possible injury; therefore, Manchester can serve as an example to other jurisdictions in terms of bicycle-related policy, safety, and infrastructure.
- The impact of other significant variables are not completely clear and need to be further investigated by utilizing similar data. This will determine if results are comparable or an alternate method needs to be implemented to assess model estimations.

As logical next steps, future work will focus on improving the defining criteria of LTS to properly assess bicycle safety and comfort. Future research is needed to explore advanced models on crash frequency, crash rate, or injury severity from other jurisdictions. This may also include disaggregating the data by LTS and generating separate models for each LTS. For example, if the sample sizes permit, create a safety model for each LTS and conduct a parameter transferability test to determine if contributing factors are statistically different by LTS.

Although a total of 65 variables were tested for significance, only statistically significant variables are included in the final model. Taking that into account, there could be variables that are not statistically significant that have an impact on bicycle injury severity; however, they are not discussed or included due to statistical insignificance. Future research can consider different combinations of variables to uncover additional bicycle injury severity contributing factors. In addition, the correlation between STRAVA and LTS identified in this paper suggests the potential of using crowdsourced data (i.e., STRAVA) in crash analysis. Therefore, due to the lack of raw STRAVA data for the current study, future research can use STRAVA as a variable in the modeling process.

Acknowledgements

The authors want to acknowledge the funding support from the Pacific Northwest Transportation Consortium (PacTrans) small project grant through the project “Geospatial Analysis of Bicycle Network Level of Traffic Stress, Bicycle Mode Choice Behavior, and Bicycle Crashes for Risk Factor Identification” and the multi-institution project “Bicycle Safety Analysis: Crowdsourcing Bicycle Travel Data to Estimate Risk Exposure and Create Safety Performance Functions”. The authors also want to thank Mr. Tim Blagden from New Hampshire Bike Walk Alliance for providing the data used in this study and the New Hampshire Department of Transportation level of traffic stress (LTS) pilot project team for their efforts in creating the procedures to code the LTS network for the four study sites.

References

Abdel-Aty, M., Keller, J., 2005. Exploring the overall and specific crash severity levels at signalized intersections. Accid. Anal. Prev. 37 (May (3)), 417–425.
Agran, P.F., Castillo, D.N., Winn, D.G., 1990. Limitations of data compiled from police reports on pediatric pedestrian and bicycle motor vehicle events. Accid. Anal. Prev. 22 (August (4)), 361–370.
Anderson, J., Hernandez, S., 2017. Roadway classifications and the accident injury severities of heavy-vehicle drivers. Anal. Methods Accid. Res. 15, 17–28. http://linkinghub.elsevier.com/retrieve/pii/S2213665717300052.
Arentze, T.A., Molin, E.J.E., 2013. Travelers' preferences in multimodal networks: design and results of a comprehensive series of choice experiments. Transp. Res. Part A: Policy Pract. 58 (December), 15–28.
Beck, L.F., Dellinger, A.M., O'Neil, M.E., 2007. Motor vehicle crash injury rates by mode of travel, United States: using exposure-based methods to quantify differences. Am. J. Epidemiol. 166 (July (2)), 212–218.
Benepe, A., Frieden, T., Kelly, R., Weinshall, I., 2005. Bicyclist Fatalities and Serious Injuries in New York City A Joint Report from the Parks and Recreation, Transportation, and the New York City Police Department. pp. 40.
Bike Manchester, 2017. Feedback Request: City Stress Map. http://www.bikemht.com/feedback-request-stress-map/.
Broach, J., Dill, J., Gliebe, J., 2012. Where do cyclists ride? A route choice model developed with revealed preference GPS data. Transp. Res. Part A: Policy Pract. 46 (December (10)), 1730–1740.
Campbell, M., Lyons, G., 2008 January. Wayfinding in unfamiliar urban environments. In: 40th Universities Transport Study Group Conference. Portsmouth, UK.
Carter, D.L., Hunter, W.W., Zegeer, C.V., Stewart, J.R., Huang, F.H., 2006. Pedestrian and bicyclist intersection safety indices. Security 99 (April). https://www.fhwa.dot.gov/publications/research/safety/pedbike/06130/06130.pdf.
Caulfield, B., Brick, E., McCarthy, O.T., 2012. Determining bicycle infrastructure preferences – a case study of Dublin. Transp. Res. Part D: Transp. Environ. 17 (5), 413–417.
Cervero, R., Duncan, M., 2003. Walking bicycling and urban landscapes: evidence from the San Francisco Bay area. Am. J. Public Health 93 (9), 1478–1483.
Chen, P., 2015. Built environment factors in explaining the automobile-involved bicycle crash frequencies: a spatial statistic approach. Saf. Sci. 79, 336–343.
Coates, N.J., May 2014. Guide to Conducting Walkability and Bikeability Assessments in New Hampshire Communities.
Dill, J., McNeil, N., 2013. Four types of cyclists? Examination of typology for better understanding of bicycling behavior and potential. Transp. Res. Rec.: J. Transp. Res. Board 2387, 129–138.
Dixon, K., Monsere, C., Xie, F., Gladhill, K., 2012. Calibrating the future highway safety manual predictive methods for Oregon State Highways, Tech. rep.Calibrating the future highway safety manual predictive methods for Oregon State Highways, Tech. rep.
Dolatsara, H.A., 2014. Development of Safety Performance Functions for Non-Motorized Traffic Safety. pp. 1–91.
Eluru, N., Bhat, C.R., Hensher, D.A., 2008. A mixed generalized ordered response model for examining pedestrian and bicyclist injury severity level in traffic crashes. Accid. Anal. Prev. 40 (3), 1033–1054.
Federal Highway Administration, 2003. Pedestrian and Bicycle Facility Guidelines. pp. 198–201.
Gelino, K., Krass, C., Olds, J., Sandercock, M., 2012. Why Can't We Be Friends? Reducing Conflicts Between Bicycles and Trucks. pp. 49.
Greene, W.H., 2012. Econometric Analysis, 7th ed. Pearson Education, New York, NY. http://pages.stern.nyu.edu/~wgreene/Text/econometricanalysis.htm.
Greibe, P., 2003. Accident prediction models for urban roads. Accid. Anal. Prev. 35 (May), 273–285.
Habib, K.N., Mann, J., Mahmoud, M., Weiss, A., 2014. Synopsis of bicycle demand in the City of Toronto: investigating the effects of perception consciousness and comfortability on the purpose of biking and bike ownership. Transp. Res. Part A: Policy Pract. 70 (December), 67–80.
Haleem, K., Abdel-Aty, M., 2010 Aug. Examining traffic crash injury severity at unsignalized intersections. J. Saf. Res. 41 (4), 347–357.
Handy, S.L., Xing, Y., Buehler, T.J., 2010. Factors associated with bicycle ownership and

use: a study of six small U.S. cities. Transportation 37 (6), 967–985.
Harkey, D., Reinfurt, D., Knuiman, M., 1998. Development of the bicycle compatibility index. Transp. Res. Rec. 1636 (1), 13–20.
Hood, J., Sall, E., Charlton, B., 2011. A GPS-based bicycle route choice model for San Francisco, California. Transp. Lett.: Int. J. Transp. Res. 3 (1), 63–75.
Jacobsen, P., 2003. Safety in numbers: more walkers and bicyclists, safer walking and bicycling. Inj. Prev. 9 (3), 205–209.
Jestico, B., Nelson, T., Winters, M., 2016. Mapping ridership using crowdsourced cycling data. J. Transp. Geogr. 52, 90–97.
Jonathan Maus, 2014. ODOT Embarks on "Big Data" Project with Purchase of Strava Dataset – BikePortland.org. https://bikeportland.org/2014/05/01/odot-embarks-on-big-data-project-with-purchase-of-strava-dataset-105375.
Kang, K., Lee, K., 2012. Development of a bicycle level of service model from the user's perspective. KSCE J. Civ. Eng. 16 (6), 1032–1039.
Kim, J.K., Kim, S., Ulfarsson, G.F., Porrello, L.A., 2007. Bicyclist injury severities in bicycle-motor vehicle accidents. Accid. Anal. Prev. 39 (2), 238–251.
Kirner Providelo, J., da Penha Sanches, S., 2011. Roadway and traffic characteristics for bicycling. Transportation 38 (5), 765–777.
Larsen, J., Patterson, Z., El-Geneidy, A., 2013. Build it but where? The use of geographic information systems in identifying locations for new cycling infrastructure. Int. J. Sustain. Transp. 7 (4), 299–317.
Li, Z., Wang, W., Liu, P., Ragland, D.R., 2012. Physical environments influencing bicyclists' perception of comfort on separated and on-street bicycle facilities. Transp. Res. Part D: Transp. Environ. 17 (May (3)), 256–261.
Lowry, M.B., Callister, D., Gresham, M., Moore, B., 2012. Using bicycle level of service to assess community-wide bikeability. Transp. Res. Rec.: J. Transp. Res. Board 2314, 15.
Lowry, M.B., Furth, P., Hadden-Loh, T., 2016. Prioritizing new bicycle facilities to improve low-stress network connectivity. Transp. Res. Part A: Policy Pract. 86, 124–140.
Lundberg, B., Weber, J., 2014. Non-motorized transport and university populations: an analysis of connectivity and network perceptions. J. Transp. Geogr. 39, 165–178.
Mannering, F.L., Shankar, V., Bhat, C.R., 2016. Unobserved heterogeneity and the statistical analysis of highway accident data. Anal. Methods Accid. Res. 11, 1–16.
McFadden, D., 1981. Econometric models of probabilistic choice. In: Manksi, C.F., McFadden, D. (Eds.), Structural Analysis of Discrete Data with Econometric Applications. MIT Press, Cambridge, MA, pp. 198–269 Chapter 5.
Mekuria, M.C., Furth, P.G., Nixon, H., 2012 May. Low-sress bicycling and network connectivity. Tech. rep., MINETA Transportation Institute Report 11-19.
Milakis, D., Athanasopoulos, K., 2014. What about people in cycle network planning? Applying participative multicriteria GIS analysis in the case of the Athens metropolitan cycle network. J. Transp. Geogr. 35 (February), 120–129.
Milne, A., Melin, M., 2014. Bicycling and walking in the United States: 2014 benchmarking report, Tech. rep., Aliance for Biking and Walking.
Moahn, D., et al., 2006. Risk factors for road traffic injuries. Road Traffic Injury Prevention:Training Manual. World Health Organization, Geneva, pp. 21–40.
Monsere, C., Wang, H., Wang, Y., Chen, C., 2017. Risk factors for pedestrian and bicycle crashes, Tech. rep. Oregon Department of Transportation.
Moore, D.N., Schneider, I.V., Savolainen, W.H., Farzaneh, P.T.M., 2011. Mixed logit analysis of bicyclist injury severity resulting from motor vehicle crashes at intersection and non-intersection locations. Accid. Anal. Prev. 43 (3), 621–630. http://dx.doi.org/10.1016/j.aap.2010.09.015.
Morris, A., 2014. N.H. Department of Transportation considers fitness app data purchase to improve biking experience. http://healnh.org/index.php/news/82-newsroom/news/471-n-h-department-of-transportation-considers-fitness-app-data-purchase-to-improve-biking-experience.
Mountain, L., Jarrett, D., 1996. Accident prediction models for roads with minor junctions. Accid. Anal. Prev. 28 (6), 695–707.
Muñoz, B., Monzon, A., López, E., 2016. Transition to a cyclable city: latent variables affecting bicycle commuting. Transp. Res. Part A: Policy Pract. 84, 4–17.
National Center for Statistics and Analysis, 2017. Bicyclists and Other Cyclists: 2015 Data (traffic safety facts. report no. DOT HS 812 (382). Tech. Rep., March. . Washington, DC, https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/812382.
New Hampshire Department of Transportation, 2016. Cooperative Project Agreement: SPR 26962R. Tech. rep. http://sos.nh.gov/WorkArea/DownloadAsset.aspx?id=8589962881.
NHTSA, 2014. Traffic safety facts, 2012 data – bicyclists and other cyclists. Tech. Rep. Publication no. DOT HS 812 018, National Highway Traffic Safety Administration. US Department of Transportation, Washington, DC.
Nordback, K., Marshall, W.E., Janson, B.N., 2014. Bicyclist safety performance functions for a U.S. city. Accid. Anal. Prev. 65, 114–122.
Oh, J., Jun, J., Kim, E., Kim, M., 2008. Assessing Critical Factors Associated with Bicycle Collisions at Urban Signalized Intersections. pp. 1–17.
Pai, C.W., 2011. Overtaking rear-end and door crashes involving bicycles: an empirical investigation. Accid. Anal. Prev. 43 (May (3)), 1228–1235.
Petritsch, T.A., Landis, B.W., Huang, H.F., Challa, S.K., 2006. Sidepath safety model: bicycle sidepath design factors affecting crash rates. Transp. Res. Rec. 1982 (1), 194–201.
Robidoux, C., 2017. City gets TAP grant for $1M rail trail expansion – Manchester Ink LinkManchester Ink Link. https://manchesterinklink.com/12-local-projects-selected-transportation-alternatives-program-funds/.
Rybarczyk, G., Wu, C., 2010. Bicycle facility planning using {GIS} and multi-criteria decision analysis. Appl. Geogr. 30 (2), 282–293.
Schepers, J.P., Kroeze, P.A., Sweers, W., Wust, J.C., 2011. Road factors and bicycle-motor vehicle crashes at unsignalized priority intersections. Accid. Anal. Prev. 43 (May (3)), 853–861.
Sener, I.N., Eluru, N., Bhat, C.R., 2009. An analysis of bicycle route choice preferences in Texas, US. Transportation 36 (5), 511–539.
Simmons, E., Kay, M., Ingles, A., Khurana, M., Sulmont, M., Lyons, W., March 2015. White paper: Evaluating the Economic Benefits of Nonmotorized Transportation.
Stone, M., Broughton, J., 2003. Getting off your bike: cycling accidents in Great Britain in 1990–1999. Accid. Anal. Prev. 35 (4), 549–556.
STRAVA, 2017. Strava | About Us. https://www.strava.com/about.
Stutts, J.C., Williamson, J.E., Whitley, T., Sheldon, F.C., 1990. Bicycle accidents and injuries: a pilot study comparing hospital- and police-reported data. Accid. Anal. Prev. 22 (1), 67–78.
The League of American Bicyclists, 2015. Bicycle Communiting Data. League of American Wheel-Men, Inc. http://bikeleague.org/commutingdata.
Tilahun, N.Y., Levinson, D.M., Krizek, K.J., 2007. Trails, lanes, or traffic: the value of different bicycle facilities using an adaptive stated preference survey. Transp. Res. Part A 41, 287–301.
Titze, S., Stronegger, W.J., Janschitz, S., Oja, P., 2008 Sep. Association of built-environment, social-environment and personal factors with bicycling as a mode of transportation among Austrian city dwellers. Prev. Med. 47 (3), 252–259.
Twaddell, H., Martin, L., Dill, J., McNeil, N., Petritsch, T., McLeod, P., Dickman, D., Gilpin, J., September 2016. Strategic Agenda for Pedestrian and Bicycle. pp. 62. https://www.fhwa.dot.gov/environment/bicycle_pedestrian/publications/strategic_agenda/.
Vandenbulcke, G., Thomas, I., Panis, L.I., 2014. Predicting cycling accident risk in Brussels: a spatial case–control approach. Accid. Anal. Prev. 62 (January), 341–357.
Verma, M., Rahul, T.M., Reddy, P.V., Verma, A., 2016. The factors influencing bicycling in the Bangalore city. Transp. Res. Part A: Policy Pract. 89, 29–40.
Wang, H., Palm, M., Chen, C., Vogt, R., Wang, Y., 2016. Does bicycle network level of traffic stress (LTS) explain bicycle travel behavior? Mixed results from an Oregon case study. J. Transp. Geogr. 57, 8–18.
Wang, Y., Nihan, N.L., 2004. Estimating the risk of collisions between bicycles and motor vehicles at signalized intersections. Accid. Anal. Prev. 36 (3), 313–321.
Washington, S., Karlaftis, M., Mannering, F., 2011. Statistical and Econometric Methods for Transportation Data Analysis, 2nd ed. Chapman and Hall/CRC, Boca Raton.
Wei, F., Lovegrove, G., 2013. An empirical tool to evaluate the safety of cyclists: community based, macro-level collision prediction models using negative binomial regression. Accid. Anal. Prev. 61, 129–137.
Wierda, M., Brookhuis, K.A., 1991. Analysis of cycling skill: a cognitive approach. Appl. Cognit. Psychol. 5 (2), 113–122.
Winters, M., Davidson, G., Kao, D., Teschke, K., 2011. Motivators and deterrents of bicycling: comparing influences on decisions to ride. Transportation 38 (1), 153–168.
Yan, X., Ma, M., Huang, H., Abdel-Aty, M., Wu, C., 2011. Motor vehicle-bicycle crashes in Beijing: irregular maneuvers, crash patterns and injury severity. Accid. Anal. Prev. 43 (September (5)), 1751–1758.