Estimating Bicycle Demand in the Austin, Texas Area: Role of a Bikeability Index

Sirajum Munira
Texas A&M Transportation Institute
505 E Huntland Dr, Austin, TX 78752
Email: munira_silvy@tamu.edu
ORCID: 0000-0002-4953-2628

Ipek N. Sener, Ph.D.
Texas A&M Transportation Institute
505 E Huntland Dr, Austin, TX 78752
Email: i-sener@tti.tamu.edu
ORCID: 0000-0001-5493-8756

Yunlong Zhang, Ph.D.
Zachry Department of Civil and Environmental Engineering, Texas A&M University
201 Dwight Look Engineering Building
College Station, TX 77843-3136
Email: yzhang@civil.tamu.edu
ORCID: 0000-0003-2404-5409

Abstract

This study contributes to research and practice by demonstrating the use of a composite measure, a bikeability index, to facilitate the use of and improve the performance of direct demand models for bicycle traffic, especially when only limited observation is available. The city of Austin was selected as a case study to develop the model using bicycle volume from 44 intersections. Existing knowledge and data were leveraged to develop the bikeability index that encompasses multiple built environment features (bicycle route length, comfort, connectivity, destination density, and transit coverage) to quantify the bike-friendliness of the network. In addition to the index, the demand model contained five demographic and land use variables. Some of the variables provided unique insights into bike travel behavior within the city, such as the significant and positive influence of the presence of bike signals and bike-accessible bridges. Along with the improved scalability and transferability of the modeling approach, the results and discussion are expected to facilitate and/or guide informed strategies and educational programs to increase nonmotorized activity in Austin as well as other regions.

Introduction

The social, environmental, economic, physical health, and road safety benefits of walking and biking have been well documented by several studies (De Nazelle et al. 2011; Jacobsen 2015; Lindsay et al. 2011; Stipdonk and Reurings 2012). Recognizing the wide range of benefits of increased nonmotorized mode share, researchers, practitioners, policymakers, and health advocates worldwide are working to create bicycling- and walking-friendly communities and reduce automobile dependency. Despite many efforts aimed at promoting nonmotorized activities in the United States, statistics based on the 2017 National Household Travel Survey showed that only around 12% of daily trips are made by walking and about 1% are made by biking (Buehler 2019). When compared with other countries, especially European countries where nonmotorized mode share is as high as 40%, US cities aiming to become more bicycling and walking friendly still have much to accomplish (Handy 2019). Nonetheless, pedestrians and bicyclists account for a disproportionate share of the total fatal and serious injury crashes. In the United States, these two modes accounted for around 19% of the total US traffic fatalities in 2018 (NCSA 2019).

Data on bicycle and pedestrian demand or volume are of utmost value to promote bicycling- and walking-friendly policies and evaluate the related efforts. Without such data, it is difficult to provide a reliable answer to the critical questions of how many people actually use current pedestrian or bicycle facilities and how many will potentially use a new or improved facility if one is built. The lack of reliable volume estimates often puts bicycle development projects at a disadvantage due to limited resources when competing with projects for motorized vehicles (Gosse and Clarens 2014). Safety professionals also need location-based volume data to accurately discern the trend in crash rates, identify high-risk locations, and understand the crash causation. As noted by Turner et al. (2017), exposure to risk is one of the most critical elements in bicycle and pedestrian safety analysis, yet it is one of the most frequently missing pieces of the puzzle.

Among several approaches to estimate and predict the demand of pedestrian and bicycle travel, the direct (facility) demand model is the most frequently used modeling approach in the area of pedestrian/bicyclist safety (Turner et al. 2017). This particular type of model utilizes count observations from limited locations and estimates demand in a specific geographic area (mid-block or intersection) by directly relating the counts with mode, trip, and traveler attributes using different forms of regression analysis (Ortuzar and Willumsen 2011). Direct demand models for nonmotorized activity have come a long way since the first related study by Pushkarev and Zupan (1971), which used 11 variables to estimate pedestrian traffic in Manhattan, New York City. Since then, a number of regions across the United States have utilized these models to estimate and predict bicycle and pedestrian traffic, but the approach varies widely in the quantity, specificity, and scale of data used. Researchers using the nonmotorized direct demand model in the last 5 years have used data from 45 locations (e.g., Hasani et al. 2019) to more than 6,000 locations (e.g., Le et al. 2018) with several explanatory variables to explain their influence on nonmotorized demand.

The modeling approach, in the context of both research and practice, often faces the issue of small sample size, meaning limited actual count data from a study area. This issue is due to the fact that site data-collection efforts require resources (e.g., time, budget, staff) that are often limited, especially when it comes to nonmotorized travel. The small sample puts constraints on the modeling process in multiple ways and negatively affects modeling results and conclusions.

While inclusion of adequate explanatory variables is essential to capture and explain the spatial variation of the nonmotorized activity, the small sample size limits the number of predictors that can be added to the regression model in order to avoid the overfitting issue (Howell 1997). This often results in the omission of important attributes that could play a critical role in explaining bicycle and pedestrian traffic variation in an area.

This particular issue might be addressed by using a composite metric or an index value made up of two or more relevant variables. In the context of nonmotorized analysis, the composite measure should be built in such a way that it can represent the bicycle friendliness or accessibility of a location or area. One such metric could be drawn from studies that developed a bikeability index (Hartanto 2017; Winters et al. 2013), which is often used to quantify a location's pleasantness and/or attractiveness to bicyclists. Although the use of composite variables is a common practice in different areas of research, including in estimating pedestrian volume (e.g., Clifton et al. 2016) when the sample size is not adequate (Song et al. 2013), to the authors' knowledge, it has not been used to enhance direct demand models for estimating bicycle activity. However, before including such metrics into the direct demand model, it is essential to ensure that the metrics be guided by the literature, relevant to local condition, and well adapted to data availability.

Another limitation of the direct demand modeling approach stems from the fact that it is not transferable, a model developed for a specific region cannot be directly used in another region with different local conditions. Therefore, each region must develop its own model that is customized to account for the local characteristics. To the authors' knowledge, no studies have estimated bicycle demand or exposure at Austin intersections, despite recent studies having shown that disregarding pedestrian exposure could significantly affect the crash analysis model (Fitzpatrick et al. 2018). A direct demand model for the city of Austin, known for its unique diversity in terms of age, culture, income, and built environment characteristics (Hedman et al. 2017), as well as its aggressive policies to promote nonmotorized activity in the local communities (City of Austin 2018a), may provide unique insights into the determinants of bicycle activity. In addition to the widely used explanatory variables discussed and explored in the available literature, new variables reflecting the distinctiveness of the bicyclist community of the city must be examined.

Acknowledging those gaps, this study contributes to research and practice by specifically bridging two areas of nonmotorized research: bikeability and direct-demand modeling. The authors developed a bikeability index, adapted it to the local conditions and data availability, and demonstrated its practical value to facilitate direct-demand models for bicycle traffic. A bikeability index that encompasses multiple built-environment variables to represent how safe, easy, and desirable a location is for biking would be beneficial both as a standalone indicator and as an essential component of a direct-demand model. This is particularly important when only limited observation is available, as in the case of this study's focus area of Austin, Texas. The outcome of the model is also expected to be practically beneficial and contribute to the city's nonmotorized-related goals by estimating bike traffic for all intersections that do not have any count observations.

Role of Bikeability Index

Studies of bicycle direct-demand models have used a wide range of explanatory variables, such as land use, sociodemographic, weather-related, motorized traffic, road type, and nonmotorized facility variables. While exhibiting the significant influence of each of these variables on nonmotorized traffic demand [see Munira and Sener (2017) for a detailed discussion of the explanatory variables], almost all studies thus far have emphasized that future studies should investigate additional and pertinent explanatory variables to better explain the nonmotorized demand. The exploration and development of a bikeability index plays an important role in responding to this need.

To summarize, quantify, and visualize the nonmotorized activity friendliness of the built environment, a number of indices have been developed, primarily in health-related studies. Generally, the index values are created by mathematically combining several attributes that support or obstruct nonmotorized activity. Guided by previous literature that reveals the association between the built environment and walking behavior, researchers have utilized a wide array of features to develop walkability index values (Emery et al. 2003; Frank et al. 2005). Often, the index value created for one region is modified or tailored to suit local conditions before being applied in another region (Owen et al. 2007; Van Dyck et al. 2010). However, compared with the walkability index, much less attention has been given to defining and mapping how bikeable a geographic location is. Harkey et al. (1998) formulated a complex index by combining nine weighted components to calculate a bicycle compatibility index of street segments. Van Dyck et al. (2012) developed a cyclability index for three countries by combining four attributes: proximity to destinations, good walking and cycling facilities, perceived difficulties in parking near local shopping areas, and perceived aesthetics. However, both of these studies used questionnaire survey results to facilitate their research, which was identified as a time-consuming and complicated process (Krenn et al. 2015).

Recognizing the ease of use and availability of spatial data management software, Winters et al. (2013) developed a bikeability index for the Metro Vancouver area to detect bicycle friendliness using five components: bike route density, bike route separation, connectivity, topography, and destination density. Mesa and Barajas (2013) developed a bikeability index for Cali, a state capital in Colombia, using four attributes: slope, environmental quality index, quality of infrastructure (road safety and maintenance), and personal safety. Krenn et al. (2015), with guidance from these cited studies, developed a bikeability index appropriate to represent the bike friendliness of a mid-sized European city. The study used five indicators that were correlated to cycling in the region: cycling infrastructure, presence of separated bicycle pathways, main roads without any parallel bicycle infrastructure, aesthetic areas, and topography. Hartanto (2017) developed a bikeability index that specifically evaluated the transit-oriented development characteristics around transit nodes in the Netherlands. San Francisco, California, uses the level of traffic stress (LTS) as a bikeability metric (Gutierrez et al. 2017). However, Gutierrez et al. (2017) acknowledged that it is difficult to estimate and track the LTS metric to monitor the city's progress toward improving the bicycle-friendly environment. Moreover, illustrating the differences in built-environment characteristics between Western and Asian countries, bike friendliness has been quantified in Taipei, Taiwan (Lin and Wei 2018), Seoul, South Korea (Kang et al. 2019), and four cities in China (Gu et al. 2018).

In addition, quantification of bike friendliness has been addressed by a few transportation agencies as well as data service platforms. For example, to quantify neighborhoods' bike accessibility, Bike Score (Goodyear 2012) was developed by the web-based service Walk Score, known for scoring neighborhood walkability. The score, published for multiple US and Canadian cities, is based on the availability of bike infrastructure, hilliness of the area, amenities and road connectivity, and number of bike commuters. The metric was also used in a study by Winters et al. (2016), who explored how Bike Score was associated with cycling behavior between and within cities by analyzing data across 24 Canadian and US cities. Other examples of similar metrics include the bikeway quality index and cycle zone analysis, developed by the Portland Bureau of Transportation (Bower et al. 2007), and the bicycle suitability score, developed for state roadways in Texas (Turner et al. 1997).

When investigating the availability of a bike and walk index for Austin, the authors found that Austin has adopted a pedestrian environmental quality index (City of Austin n.d.) originally developed by the San Francisco Department of Public Health to assess pedestrian desires and needs, as well as to identify deficiencies in infrastructure. However, to the authors' knowledge, no effort has been made to create bikeability indices that would help quantify bicycle friendliness of a street network for the region.

The above discussion highlights the importance of a new avenue of research that may utilize built environment attributes that individuals consider important for bicycling to quantify a bikeability index to eventually be used to improve the performance of the direct-demand model, especially when available count observation is limited. Such a composite variable is also useful because it not only controls Type I errors and increases accuracy in estimation (Song et al. 2013) but also combines multiple highly correlated variables into more meaningful information.

Methodology

Study Area

The city of Austin was selected as the study area for this research. With an area of 844 km^2 (326 mi^2), the city has a population of more than 981,035 (City of Austin Planning and Zoning 2019). Downtown Austin is the central business district of the city and is located on the north bank of the Colorado River. The University of Texas (UT) at Austin is located north of the downtown area and accommodates more than 50,000 students.

As mentioned previously, despite being heavily car dependent, the city is working to increase bikeability and is designated as a Gold-Level Bicycle-Friendly Community by the League of American Bicyclists (2015). In 2017, Austin ranked 13th among US cities in terms of number of bicycle commuters on the street (League of American Bicyclists 2017). The Austin Transportation Department has taken a holistic approach to promote nonmotorized activity among the population of all ages and abilities and aims to provide safe, efficient, and sustainable bikeways and walkways. The latest master plan (2014 Austin Bicycle Master Plan) adopted by the Austin City Council aims to develop a connected and protected walking and biking network for residents (City of Austin 2014). According to the department's 2018 annual report (City of Austin 2018a), the region has a total of 430.5 km (267.5 mi) of bicycle facilities, including protected and buffered bicycle lanes and urban trails (shared-use paths). Since 2009, the city has observed a significant increase in bicycle commuters. The citywide mode share of bicycling doubled in 2011 (around 2%) compared with 2009 (City of Austin 2014). In some census tracts in the central region, the bicycle commuting mode share is considerably higher compared with suburban regions (City of Austin 2014). However, according to the ACS (2019), the bike mode share across the counties of City of Austin varied from 0.2% to 0.9% in 2019. The city also adopted the Vision Zero initiative to reduce traffic-related deaths and injuries to zero by the year 2025 (City of Austin 2016).

Bicycle Volume Counts (Dependent Variable)

Two types of bicycle count data were obtained for the study area. The short-count (24-hour) data were obtained from the City of Austin Transportation Department, and continuous-count data were obtained from Eco-Counter, which is a company that assists with continuous data collection for pedestrian and bicyclists in specific locations across cities around the world (Eco-Counter 2019). The continuous-count data were needed to calculate adjustment factors that could be incorporated with the short count to estimate the annual average daily bicycle (AADB) volume for the specific locations (Nordback et al. 2013).

The 24-hour bicycle count data were available for 44 locations. According to city officials, the sites were selected using the City of Austin bicycle route map (City of Austin 2017) and based on the professional judgment of local planners. Following standard procedures, the data were collected by the city using a video recorder in each of the intersections on typical weekdays distributed over 5 months (April–June, August, and October) in 2017. The permanent location counts were obtained from Eco-Counter for 11 locations in the Austin area; the company provided continuous counts for the locations since 2012. The count data from the permanent counters were used to estimate the daily and monthly factors, which were then applied to calculate the AADB volume for each location where the short-count data were available.

Fig. 1 shows the location of the 44 intersections with short-count data and presents the estimated AADB for each location. The intersections exhibited notable variation in terms of AADB volume, with a minimum of 43 and maximum of 1,282 riders. Table 1 lists the descriptive statistics for the bicycle counts.

Table 1. Description of estimated AADB volume.

No. of Intersections	Mean	Min/Max	Variance
44	309	43/1,282	82,867

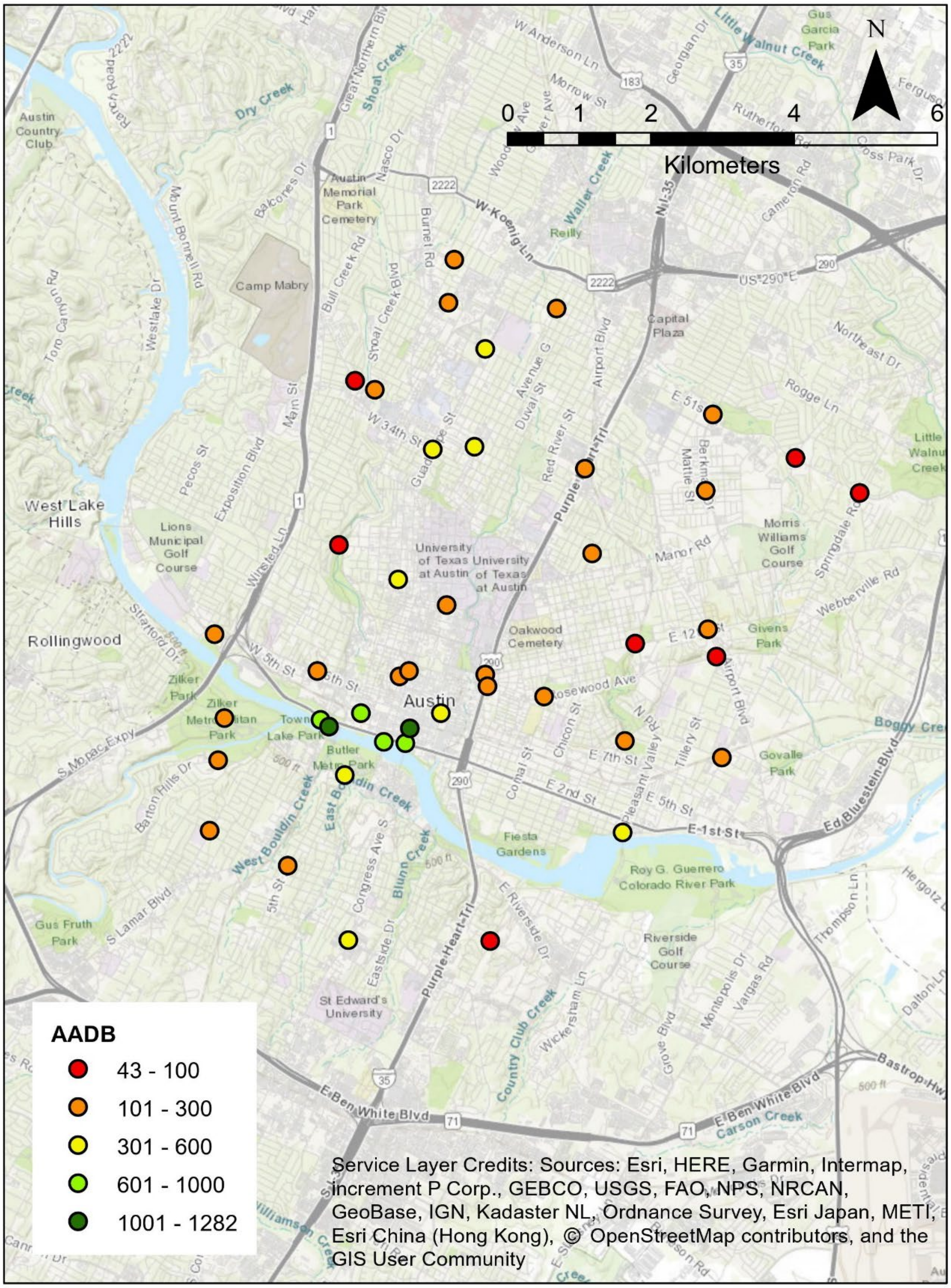

Fig. 1. AADB volume at 44 intersections in Austin.

Explanatory Variables

In an effort to assemble explanatory variables for the study, prior studies focusing on direct-demand models and bike determinants were reviewed (Chen et al. 2017; Dill 2009; Hankey et al. 2017; Hasani et al. 2019; Tabeshian and Kattan 2014). This study sought to build a rich set of explanatory variables using insights from the earlier studies as well as the data available for the study area. To develop the explanatory variables for the model, first a comprehensive search was performed to see which data were publicly available. Data were gathered from the City of Austin data portal, 2017 American Community Survey, City of Austin Planning and Development Review Department, Texas Education Agency, Austin Transportation Department Arterial Management Division, Capital Metro, and BCycle (Austin bike-sharing agency) data portal. After identifying the gap between the required and available datasets, relevant authorities were contacted and asked to provide additional data for research purposes. The City of Austin Transportation Department's Data and Technology Services provided an updated bicycle infrastructure map. Apart from the infrastructure type, the map also includes information regarding bicycle comfort level developed and used by the internal departments of Austin. In addition, a review of factors included in past studies identified a need to explore new variables related to the features that have the potential to drive the bicycle demand at an intersection. Therefore, this study examined some additional variables, including the presence of bike-sharing stations or bike signals around an intersection, and bike-accessible bridges, anticipating their possible impacts on bicycle volume in the area.

Since all of the raw datasets obtained from different sources were at different spatial scales, the datasets were cleaned and processed to bring them to homogenous spatial scales (buffer level). More than 400 variables for three buffer zones, 161 m (0.1 mi), 804 m (0.5 mi), and 1,609 m (1 mi), were created. The variables were categorized into seven groups following the categorization suggested by Munira and Sener (2017): demographics, socioeconomics, network/interaction with vehicle traffic, pedestrian- or bicycle-specific infrastructure, transit facilities, major generators, and land use.

The demographic and socioeconomic variables included age, gender, education, race, household size and occupancy status, income, and commute mode and time of the surrounding population. The network and bicycle-specific infrastructure-related variables included different types of bicycle infrastructure based on the conditions and comfort level, which was developed by the City of Austin (2017), as well as bike signal, intersection density, and bike-sharing stations. Various transit-facility-related variables were compiled, including frequency of transit stops, transit route length, and distance from hub locations. Major generators and land use variables, such as number of schools, offices, industries, open areas, mixed-use developments, water areas, and bicycle-accessible bridges, were also gathered based on available data.

The following section provides the details of the bikeability index developed for this study.

Bikeability Index

The bikeability index was mainly inspired by the approach of Winters et al. (2013), who used empirical studies to develop a bikeability index value with five attributes: density of bicycle facilities, separation from motor vehicle traffic, connectivity of bicycle-friendly roads (local streets, bicycle routes, and off-street paths), slope, and density of destination locations. The approach to obtain the index was modified based on the data availability and local conditions. Because the main focus of the study was to demonstrate the use of a bikeability index to improve direct demand models, the spatial distribution for all attributes was taken as a 1,609-m (1-mi) buffer width around each intersection. The buffer width was selected after investigating the individual influence of all attributes on the bicycle volume. The following subsections describe the attributes used in the bikeability index for the Austin area, with a brief explanation of why they were chosen.

Bicycle Route Length. Bicycling networks are generally different from the regular street maps and are composed of various bicycle-related facility segments (i.e., off-street facilities, on-street facilities, special facilities) and regular streets that allow bicyclists (interstates and highways are not included). A bicycle network map, obtained from the City of Austin Transportation Department, was used to estimate the total length of bicycle facilities in a 1,609-m (1-mi) radius circular buffer around all intersections.

High-Comfort Bicycle Route Length. One of the interesting features of the bicycle network provided by the city was that it defined the comfort level of each segment, as described in a study by Geller (2009). The comfort level estimation considered a number of factors, including traffic speeds and volumes, roadway widths, bicycle facility type, and other readily available metrics, to determine how comfortable a segment is for people of all ages and abilities. The comfort level was mainly categorized into four types: high-comfort sections, medium-comfort sections, low-comfort sections, and extremely low-comfort sections.

This attribute estimated the total length of high-comfort segments in a 1,609-m (1-mi) radius circular buffer around all intersections. The categories included (1) off-road, (2) on-road with physical separation from motorized traffic, or (3) quiet streets with very low motorized traffic speeds and volumes. This attribute differed slightly from Winters et al. (2013), who used estimated high-quality routes physically separated from motor vehicle traffic. The high-comfort bike route length also accounts for topography (slope) of the segment, which is another indicator used by Winters et al.

Connectivity of Bicycle-Friendly Streets. This indicator was defined as the number of intersections (with three or more legs) where at least one road was favorable for cycling. Intersection density is a well-known measure of street connectivity. This study estimated the connectivity in a 1,609-m (1-mi) radius circular buffer around all intersections.

Destination Density. Destination density refers to land use types that are pertinent to cycling decisions. Acknowledging the relationship between bike activity and land use, Winters et al. (2013) estimated this indicator by utilizing parcel-level land use data of four categories: neighborhood commercial, education, entertainment, and office.

This study was guided by the same rationale while quantifying the destination density of the bikeability index developed for the study area. To create this indicator, the land use database was gleaned from the City of Austin data portal, which identifies various land use types at the parcel level. The relationship between each land use type and bike volume was then examined and indicated a strong association between bike ridership and the commercial, mixed-use, and office land use types within 1,609 m (1 mi) of the intersection. The finding was intuitive, since a handful of previous studies have also suggested the attractiveness of mixed land use (Krizek 2003), office land use (Cui et al. 2014), and commercial land use (Pulugurtha and Repaka 2008) to both bicyclists and pedestrians. Therefore, those land use types were identified as strong potential destinations for cycling and thus included in the development of the bikeability index.

It is important to note that commercial land use includes wholesale and retail trade and services. Apart from the trade location for most-durable and nondurable goods, this type also includes entertainment and recreation services, business services, commercial sports recreation and exercise, and amusement services. The mixed-use land use represents areas that contain both commercial and residential uses. The office land use includes the following business types: accounting; architectural services; design services; engineering; insurance; law offices; organization/association offices; personnel; property management; real estate; secretarial services; telephone answering services; television/film/sound recording studios; travel agencies; financial services; banks, savings and loans, and credit unions; blood banks; treatment and guidance centers; doctor, dental, psychological, and other medical offices; and electronic, pharmaceutical, chemical, and other research and development services.

Transit Coverage. Although this indicator was not included in the study by Winters et al. (2013), a transit route attribute was included in this study to acknowledge the relationship between bike activity and transit facilities (McNeil et al. 2017). Moreover, Capital Metro, Austin's regional public transportation provider, offers bike-friendly buses and trains and was recognized as a Gold-Level Bike-Friendly Business by the League of American Bicyclists (Capital Metro 2017). Thus, transit length around an intersection was deemed as a good indicator to encourage bike activity. It is important to note that a bikeability index without the transit coverage variable was also developed and tested in the model. The model with the developed index (including the transit coverage variable) exhibited superior performance.

To create this attribute, transit data were obtained from the Capital Metro Transit Authority. This route type includes several services, such as rail, local, crosstown, special, high frequency, feeder, flyer, night owl, UT shuttle, and express service.

Classification and Scoring. Each of the five attributes discussed previously was reclassified to create a scale of 1 to 10 based on the quantile value, where 1 = least bikeable environment and 10 = most bikeable environment. The scale value for each attribute was then summed to create the final index value by assigning an equal weight to each attribute. The index value could range from 5 to 50. Fig. 2 presents the bikeability index for the study area.

Model Building and Validation

In cases such as this one where the dependent variable (bicycle count) is discrete in nature, Poisson's and negative binomial models have been preferred over ordinary least squares (OLS) regression (Hankey et al. 2012; Kim and Susilo 2013). For this study, the difference between variance and mean (variance $\gg$ mean) suggested that over-dispersion was present, so a negative binomial model was utilized. Univariate and bivariate correlation analyses were performed to examine the distribution or pattern of the variables and explore how the explanatory variables interact among each other and with the dependent variable. Based on their influence on bike activity, several variables were recategorized or aggregated to create new variables, and their influence on models of varying combinations were examined. For example, the variable of population younger than 15 years old, both male and female, showed a significant relationship with bike activity and improved model performance compared with other combinations (such as population older than 18 and younger than 20) or individual age groups (such as male population of 5–9 years old). The model building and evaluating process also involved the professional judgment of the authors in relation to assessing the policy relevancy and practicality of the variables included in the final model (e.g., when building age- or education-related variables). Table 2 provides a descriptive summary of the model variables.

The final model, obtained after numerous model trials, was selected based on its predictive accuracy in terms of mean absolute error (MAE), root mean square error (RMSE), and fitness (adjusted R2). Statistical significance of individual variables and intuitive interpretation, based on insights from literature, were also considered while selecting the variables for the best model. Hence, the decision to omit or include variables from the final model was reasoned with seeking the balance between the statistical robustness of the model as well as the practical value for better decision making.

The performance of the models was evaluated using cross-validation, which is a resampling technique that helps to identify a parameter value, ensuring a proper balance between bias and variance (Chan-Lau 2017). For cross-validation, a subset of the data, known as the training set, was used to train the model, and the remaining data points served as a test set or validation set. The model on the training set seeks a minimum mean squared error (MSE). A 10-fold, cross-validation method was used to evaluate and compare the performance of the developed models. This method split the feature vector sets into 10 approximately equal-sized distinct partitions. While one set was used for testing, the other set was used for training. Then, the procedure was repeated 10 times, and all accuracy rates over these 10 runs were averaged to provide a more reliable estimate. The performance evaluation criterion was the average accuracy.

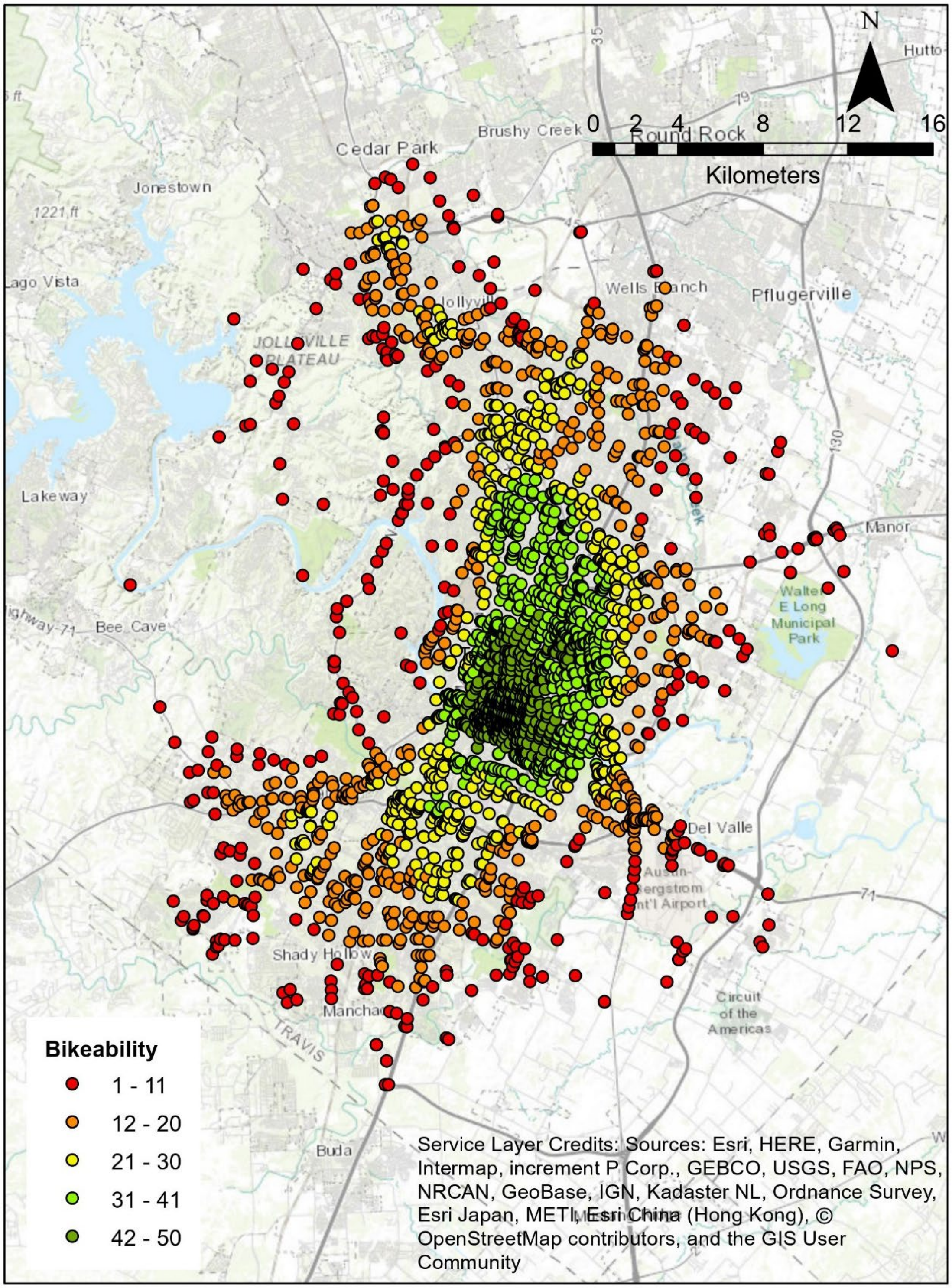

Fig. 2. Bikeability index map.

Table 2. Descriptive statistics of the model variable.

Variable	Buffer width	Mean	Max	Mean
Bikeability index	1,609 m (1 mi)	15	50	39.91
Black or African American population (in 100 s)	1,609 m (1 mi)	0.91	36.6	13.08
Population with no or some academic degree	161 m (0.1 mi)	4	38	14.3
Total population of age 14 and under (in 100 s)	804 m (0.5 mi)	0.23	10.97	3.98
Bike signal (binary variable)	161 m (0.1 mi)	1 = Presence of at least one bike signal 0 = No bike signal		
Presence of bicycle accessible bridge	161 m (0.1 mi)	1 = Presence of at least one bridge 0 = No bridge		

Results

Table 3 presents the developed negative binomial regression model to estimate the AADB volume in the Austin area intersections.

Table 3. Negative binomial regression model.

Variable	Buffer width	Estimates	T-Stat
(Intercept)		4.96	8.82
Bikeability index	1,609 m (1 mi)	0.02	1.65
Black or African American population (in 100 s)	1,609 m (1 mi)	−0.02	−3.23
Population with no or some academic degree	161 m (0.1 mi)	0.03	2.98
Total population of age 14 and under (in 100 s)	804 m (0.5 mi)	−0.12	−2.99
Bike signal	161 m (0.1 mi)	0.30	2.46
Presence of bicycle accessible bridge	161 m (0.1 mi)	0.54	2.25

Note: Model Statistics: N (sample size) = 44; Adjusted R^2 = 0.7; RMSE = 171; MAE = 132.

The final model contained six variables, five of which were significant at the 95% confidence level and one that was significant at the 90% confidence level. The adjusted R2 for the prediction model was 0.7, and RMSE was 171. The model statistics also showed a good model fit providing a good estimate of bicycle demand at all intersections.

The model also presented interesting insights into how different features influence bicycle travel within the Austin region. The annual average bicycle volume in the Austin region intersections is characterized by sociodemographic (total population of age younger than 15, Black or African American population, and adult population of age 25 or older with no or some academic degree), bicycle infrastructure (bike signals), and built environment (bikeability index and presence of bicycle-accessible bridge) variables. The varying buffer scales of the variables insinuates the importance of using different buffers in obtaining the best model, which is a finding consistent with previous studies (Liu and Griswold 2009; Miranda-Moreno and Fernandes 2011).

While findings for some variables conformed to previous studies, some other model variables provided unique insights into bike travel behavior within the Austin region. First, the bikeability index developed for this study was deemed an important variable. The results indicated the significant impact of the bikeability index (i.e., combined effect of attributes including bicycle route length and comfort, connectivity of bicycle-friendly streets, destination density, and transit coverage) around a 1,609-m (1-mi) buffer width of an intersection on bicycle volume. Although no previous studies have demonstrated this combined impact, they have confirmed the influence of these built environment features individually (e.g., Behnam and Patel 1977; Desyllas et al. 2003; Hankey et al. 2017; Lindsey 2011; Liu and Griswold 2009; Tabeshian and Kattan 2014). In addition to the other variables, the contribution of transit coverage to the bikeability index highlights the need to include such a variable to quantify bike friendliness, especially for cities such as Austin where buses and trains offer bike-friendly services. Overall, the index value not only improved the accuracy and fitness of the model but it also indicated how people's decisions to bike are formulated by the combined effect of several features of the built environment of a location.

The model also revealed a significant influence of three sociodemographic variables on bicycle volume. The negative impact of the African American population addresses the mobility issues of the minority population and conforms to a previous study by Lindsey (2011), who also found a significant negative influence of African American residents on bicycle volume in Minneapolis. It is noteworthy to mention here that, for the study area, the income variable was found to be highly correlated with other variables, especially with the variable of the African American population. Its inclusion was also leading to model instability resulting in inferior performance of the models. The dynamics of the income variable, that lead to its exclusion from the final model, emphasizes the need for a dedicated focus on understanding the role of income across the communities and whether it captures the local needs/trends or shadows some other influential effects.

In addition, the results revealed a higher bicycling propensity among the adult population (25 years and older) with a lower education level. This is not surprising since lower-educated people, most often with low-income jobs, might be less able to afford cars and thus be forced to walk or bike for their daily travel. US Census statistics also indicate that low-income households are more likely to commute by bicycle compared with high-income households (Jaffe 2015).

The results also showed that a population younger than age 15 within 804 m (0.5 mi) of an intersection was negatively associated with the bicycle volume. This result might be expected when the trend of children walking and biking to school in the United States is explored. One report showed that in 2009 only 13% of students (ages 5 through 14) walked or bicycled to school, which is a stark decrease from 48% in 1969 (National Center for Safe Routes to School 2017). Even more alarming, the percentage of walking and biking students living less than 1,609 m (1 mi) from a school has decreased from 41% to 31% during the same period. Studies have indicated that the growing number of cars and related safety issues near schools at pick-up and drop-off times are responsible for the decline in parents' willingness to allow kids to walk or bike to and from school independently (National Center for Safe Routes to School 2010; Vanwolleghem et al. 2014). The negative influence of that particular age group on bicycle volume in the Austin area may be attributed to those same factors.

The significant influence of the last two variables (bike signal and presence of bicycle-accessible bridge) offered interesting perspective into how some of the policies taken by the city might have a noteworthy impact on people's choice to bike. The results indicate that the number of bike signals positively influences bike volume around intersections. The City of Austin Transportation Department installed bicycle signals in several locations in 2017 to improve safety for both bicyclists and other road users (City of Austin 2018b). Some of the intersections have a leading pedestrian and bicycle interval to ensure that pedestrians and bicyclists have extra time to start crossing. The model results might be an implication of bicyclists' perception of being prioritized at such intersections, which might encourage biking around the area.

Moreover, the positive association between the presence of bicycle-accessible bridges, located over lakes or creeks, and bicycle volume can be interpreted in two ways. First, people might be more likely to bike near locations on or around water bodies, and second, they might tend to appreciate the greater accessibility provided by the crossing facilities that the city is building [for some improvements implemented by the city, see City of Austin Public Works Department (2017) and City of Austin Transportation Department (2016)]. Thus, these two variables support the effectiveness of some of the policies taken by the transportation department to improve the safety and mobility of bicyclists.

In addition, insights were drawn from the relationship between residential land use, one of the explanatory variables tested for the model, and bike volume in the study area. Although mixed land use exhibited a strong influence, both as a standalone model variable and as a part of the destination density, residential land use did not have a significant (i.e., at the 90% confidence level) influence on bike ridership. This finding insinuates that although people living or working in a mixed-land-use area are more likely to bike, a high-density, residential-only development does little to promote the overall nonmotorized activity of an area, which is also consistent with results from previous studies (Forsyth et al. 2007; Krizek 2003).

Model Prediction

The model was also used to predict AADB at other intersections without counts. The intersections were identified using the bike route map created by the City of Austin (2017). The bike route map comprises all bike facilities, including extremely low-comfort roads that are not recommended for bicycle travel but have no practical alternatives for some trips. Relevant explanatory variables for 2,518 intersections within the study area were gathered to utilize the developed model and predict the AADB volume. Fig. 3 shows the predicted AADB at these intersections. As seen in the figure, the predicted AADB varied from a minimum of 15 (mainly at the areas away from the downtown core) to a maximum of 1,398 (at the downtown core), which seems reasonable and intuitive; the actual count data also illustrated a high concentration (maximum of 1,282 riders) of bike ridership in the downtown core. It is important to note that since the locations of counts were identified based on the city's bicycle route map, the counts are drawn from locations within the limits of the map and do not include areas farther into the suburban regions.

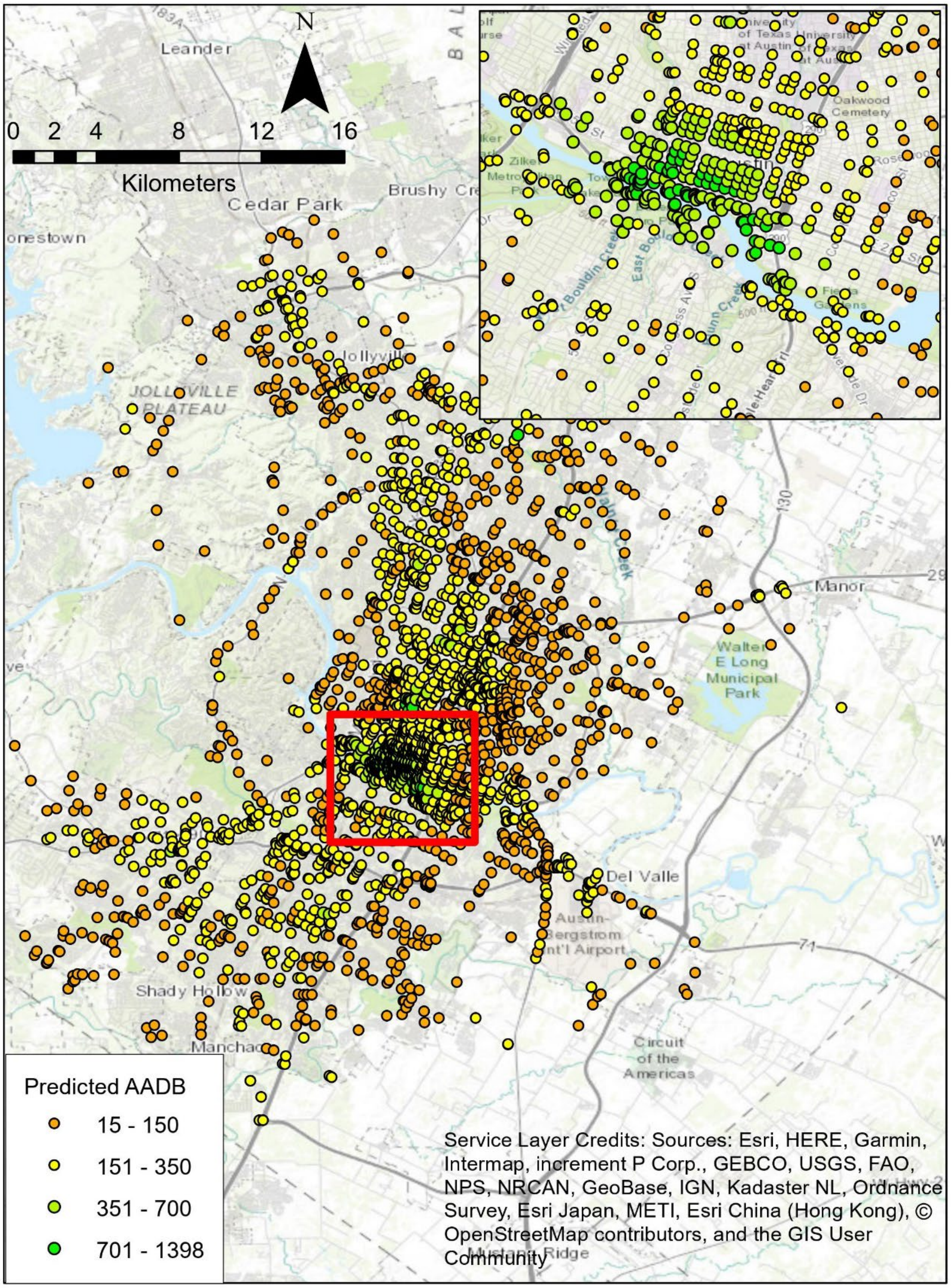

Fig. 3. Predicted annual average daily bicycle (AADB) volume.

Discussion and Conclusions

This study intended to contribute to the field of direct-demand modeling for nonmotorized traffic, especially for cases where limited observations or count data are available. The bikeability index, a composite measure encompassing multiple pertinent built environment features, emerged as a useful tool for improving the performance of the models as well as quantifying the bicycle friendliness of the entire street network for the region, which is often needed for evaluating development scenarios and policies. Moreover, the proposed framework provides an important step toward the development of a more generalized direct-demand modeling approach. The final estimation of the model still must be unique to the region because the variable values in the model equation are specific to each region; however, the underlying theory and its application, including the formulation of the bikeability index and integration of it into direct demand modeling, provides a generic approach that can be used in any region. Moreover, the bike friendliness measure, which could be termed in different forms, such as level of service, rating, and score, is often readily available from local urban planning and/or transportation agencies. Therefore, by using the bikeability index, analysts can circumvent the step of seeking a wide range of built-environment-related variables for developing direct-demand models. As a result, the scalability and transferability of the models are improved. Therefore, this index serves as an excellent basic variable to be included in direct-demand models, in combination with additional variables, regardless of the study area.

In addition, the predicted facility (intersection for this study) bike volume for the entire region is expected to be useful not only to safety analysts but also to transportation and urban planners in several applications, for example nonmotorized policy formulation, project prioritization, infrastructure management, land use planning, and air quality evaluation. The results can also help the City of Austin facilitate the goal of incorporating data for informed decision making for nonmotorized transport, as outlined in its latest Strategic Mobility Plan (City of Austin 2019).

Besides demonstrating the usability of the bikeability index measure, the developed model offers important insights into the determinants of bicycle activity within the region, providing guidance for both practitioners and researchers in transportation and urban planning to formulate and design effective strategies, training, and educational programs geared toward creating a friendlier environment for bicyclists. For example, the younger population's unwillingness to bike underscores the need for initiatives such as the Safe Routes to School program (City of Austin 2019). The program has already launched campaigns, such as Bike to School Day, in partnership with elementary and middle schools to encourage students, parents, and staff to ride their bicycles to school. Moreover, the Safe Routes to School program, in its first infrastructure report in 2019 (KLBJ 2019), detailed school-access projects related to biking and walking, such as adding sidewalks, bike lanes, pedestrian crossing signals, raised crosswalks, traffic-calming devices (such as speed cushions), and more. Another data collection effort is needed to observe how the programs and the projects have contributed to increasing the number of children biking or walking to school. Moreover, the significant influence of the African American population recognizes the value of equity considerations for addressing mobility challenges faced by racial minority populations. In addition to the race variable, the impact of lower-educated population on bike volume emphasizes the need for community outreach programs in order to expand access and use of bicycle-related services, for example, bike-sharing services. Austin's bicycle-sharing service has already initiated bilingual outreach and education campaigns as well as subsidized membership and cash payment options to increase safety and comfort and overcome cost barriers

(Shaheen and Cohen 2019). Expanding and enhancing such programs may promote bicycle use, along with shared services, across all communities in the region.

Two new variables (i.e., presence of bike signals and bicycle-accessible bridges) examined for this study also reveal the potential for several of the city's current and future policies to promote bicycling. The findings demonstrate that features such as bike signals that provide a head start to bicyclists at an intersection are likely to attract more cyclists. The city might evaluate the feasibility and the need to install additional bike signals at intersections where bicycle volume is high. Moreover, the impact of the presence of bicycle-accessible bridges implies that a close proximity to water and accessibility provided by the infrastructure yield higher bicycle traffic around an area. As acknowledged by the city (City of Austin 2019), there is a significant need to improve bicycle infrastructure gaps in several locations in the region to enhance bicycle network connectivity and overcome barriers to cycling. The results of the current study provide support to the city's plan in removing infrastructure gaps by providing bike-accessible bridges and infrastructure and emphasize the important role of such efforts in encouraging bicycling in the region. Another new variable tested for the study area, the presence of bike-sharing stations near intersections, was not found to be significant. This finding might be attributed to the fact that the bike-sharing system in Austin mainly covers the downtown region, with only 63 stations as of 2018 (BCycle 2018). However, in cities such as Houston, Los Angeles, or New York, with large-scale coverage of bike-sharing facilities, the relationship between bike volume and the presence of bike-sharing stations may be significant, thus warranting further examination. Moreover, the contribution of the transit coverage variable in developing the bikeability index demonstrates the need to extend available index measures in order to adapt to local conditions.

Finally, the model exhibited a good statistical fit and predictive accuracy and made beneficial use of the available data sources. Overall, the insights provided by the study may facilitate or act as guidance for developing demand models for similar growing cities in the United States. However, as noted in a recent Federal Highway Administration guide (Turner et al. 2017), adaptation of an available model for a region requires a profound understanding of the objectives and performance of the model as well as suitability to be used for the region of interest.

This study is not without limitations. First, the study utilized parcel-level land use data to quantify the destination density of the bikeability index for the study area. However, the attractiveness of destinations for bicyclists may be better captured by measuring actual employment size or floor area of the land use type, information that was not available at the time of this study. Future studies addressing either direct-demand models or bikeability assessment may benefit from such information to better characterize the relationship between land use and bike volume at a location. Second, given the limitation of resources (e.g., time, budget, staff), the data collection covered only a limited number of locations, which may not be fully representative of the entire region. To better capture the spatial variation of bike volume, a robust site collection approach involving sampling strategy and a larger data-collection program are warranted for selecting a representative sample of the study area. Finally, caution must be employed when models are transferred far into the future; the differences between current and future characteristics of people and locations may result in inaccurate estimates because the changes in technology and society might have unanticipated influences on user behavior.

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References

ACS (American Community Survey). 2019. "Commuting characteristics by sex, 2019 ACS 1-year estimates." Accessed February 10, 2021. https://data.census.gov/cedsci/table?q=Commuting%20Characteristics%20by%20Sex&tid=ACSST1Y2019.S0801&hidePreview=false.

BCycle. 2018. "Austin B-cycle expands service to UT Campus and West Campus neighborhoods." Accessed February 14, 2018. https://www.bcycle.com/news/2018/02/14/austin-b-cycle-expands-service-to-ut-campus-and-west-campus-neighborhoods.

Behnam, J., and B. Patel. 1977. "A method for estimating pedestrian volume in a central business district." *Transp. Res. Rec.* 629: 22–26.

Bower, D., R. Geller, L. Ginenthal, D. Igarta, M. Lear, and J. Waltz. 2007. "Portland's platinum bicycle master plan: Existing conditions report." Accessed September 27, 2020. https://www.portlandoregon.gov/transportation/article/369982.

Buehler, R. 2019. "A first look: Trends in walking and cycling in the United States 2001–2017." In *National Household Travel Survey (NHTS) Data for Transportation Applications Workshop*, 1–20. Washington, DC: National Household Travel Survey Workshop Committee.

Capital Metro. 2017. *The best month on two wheels*. Austin, TX: Capital Metro.

Chan-Lau, M. J. A. 2017. *Lasso regressions and forecasting models in applied stress testing*. IMF Working Paper. Washington, DC: International Monetary Fund.

Chen, P., J. Zhou, and F. Sun. 2017. "Built environment determinants of bicycle volume: A longitudinal analysis." *J. Transp. Land Use* 10 (1): 655–674. https://doi.org/10.5198/jtlu.2017.892.

City of Austin. 2014. "2014 Austin bicycle plan." Accessed January 15, 2020. http://austintexas.gov/page/austin-bicycle-plan.

City of Austin. 2016. "2016–2018 action plan." Accessed May 19, 2016. https://austintexas.gov/sites/default/files/files/Imagine_Austin/VisionZero/ActionPlan_5.19.16adoption.pdf.

City of Austin. 2017. "Austin Texas bike map." Accessed January 15, 2020. https://austin.maps.arcgis.com/apps/webappviewer/index.html?id=c7fecf32a2d946fabdf062285d58d40c&extent=3052120.7123%%202C10036958.1486%2C3179054.0456%2C10097891.4819%2C102739.

City of Austin. 2018a. "The City of Austin Transportation Department 2018 annual report." Accessed January 15, 2020. https://1d0d7cb9-bfde-4667-8eeb-20a5ee919bd6.filesusr.com/ugd/956239_455271f084ea4a4d9caf7bb098fb18ab.pdf.

City of Austin. 2018b. "Austin mobility news." Accessed May 4, 2021. https://mailchi.mp/austintexas/mobilitynews_09172018.

City of Austin. 2019. "The Austin Strategic Mobility Plan (ASMP)." http://www.austintexas.gov/department/austin-strategic-mobility-plan.

City of Austin. n.d. "Pedestrian environmental quality index data collection manual." Accessed January 15, 2020. https://www.austintexas.gov/edims/document.cfm?id=182245.

City of Austin Planning and Zoning. 2019. “Demographics.” Accessed January 20, 2020. http://www.austintexas.gov/department/demographics.

City of Austin Public Works Department. 2017. “Mopac mobility bridges.” Accessed January 20, 2020. http://austintexas.gov/page/mopac-mobility-bridges.

City of Austin Transportation Department. 2016. “South Lamar corridor improvement program.” Accessed January 20, 2020. https://www.austintexas.gov/edims/document.cfm?id=253598.

Clifton, K. J., P. A. Singleton, C. D. Muhs, and R. J. Schneider. 2016.“Representing pedestrian activity in travel demand models: Framework and application.” *J. Transp. Geogr.* 52: 111–122. https://doi.org/10.1016/j.jtrangeo.2016.03.009.

Cui, Y., S. Mishra, and T. F. Welch. 2014. “Land use effects on bicycle ridership: A framework for state planning agencies.” *J. Transp. Geogr.* 41: 220–228. https://doi.org/10.1016/j.jtrangeo.2014.10.004.

De Nazelle, A., et al. 2011. “Improving health through policies that promote active travel: A review of evidence to support integrated health impact assessment.” *Environ. Int.* 37 (4): 766–777. https://doi.org/10.1016/j.envint.2011.02.003.

Desyllas, J. D. D., E. Duxbury, J. Ward, and A. Smith. 2003. *Pedestrian demand modelling of large cities: An applied example from London*. London: Centre for Advanced Spatial Analysis.

Dill, J. 2009. “Bicycling for transportation and health: The role of infrastructure.” *J. Public Health Policy* 30 (1): S95–S110. https://doi.org/10.1057/jphp.2008.56.

Eco-Counter. 2019. “Products.” Accessed January 19, 2020. https://www.eco-counter.com/en/produits/multi-range/urban-multi/.

Emery, J., C. Crump, and P. Bors. 2003. “Reliability and validity of two instruments designed to assess the walking and bicycling suitability of sidewalks and roads.” *Am. J. Health Promot.* 18 (1): 38–46. https://doi.org/10.4278/0890-1171-18.1.38.

Fitzpatrick, K., R. Avelar, and S. M. Turner. 2018. *Guidebook on identification of high pedestrian crash locations*. Washington, DC: Federal Highway Administration.

Forsyth, A., J. M. Oakes, K. H. Schmitz, and M. Hearst. 2007. “Does residential density increase walking and other physical activity?” *Urban Stud.* 44 (4): 679–697. https://doi.org/10.1080/00420980601184729.

Frank, L. D., T. L. Schmid, J. F. Sallis, J. Chapman, and B. E. Saelens. 2005. “Linking objectively measured physical activity with objectively measured urban form.” *Am. J. Preventive Med.* 28 (2): 117–125. https://doi.org/10.1016/j.amepre.2004.11.001.

Geller, R. 2009. “Four types of cyclists.” Accessed January 19, 2020. https://www.portlandoregon.gov/transportation/44597?a=237507.

Goodyear, S. 2012. “Walk score launches bike score: How bikeable is your city?” Accessed January 19, 2020. https://www.bloomberg.com/news/articles/2012-05-14/walk-score-launches-bike-score.

Gosse, C. A., and A. Clarens. 2014. “Estimating spatially and temporally continuous bicycle volumes by using sparse data.” *Transp. Res. Rec.* 2443 (1): 115–122. https://doi.org/10.3141/2443-13.

Gu, P., Z. Han, Z. Cao, Y. Chen, and Y. Jiang. 2018. “Using open source data to measure street walkability and bikeability in China: A case of four cities.” *Transp. Res. Rec.* 2672 (31): 63–75. https://doi.org/10.1177/0361198118758652.

Gutierrez, C., S. Gu, L. Karam, D. Lee, and T. Thomas. 2017. “Measuring and evaluating bikeability in San Francisco.” Accessed March 23, 2017. http://sustainablecities.weebly.com/uploads/1/2/3/3/12335040/stanford_sustainable_cities_bikeability_report.pdf.

Handy, S. 2019. “Making US cities pedestrian- and bicycle-friendly.” In *Transportation, land use, and environmental planning*, edited by E. Deakin, 169–187. Amsterdam, Netherlands: Elsevier.

Hankey, S., G. Lindsey, X. Wang, J. Borah, K. Hoff, B. Utecht, and Z. Xu. 2012. “Estimating use of nonmotorized infrastructure: Models of bicycle and pedestrian traffic in Minneapolis, MN.” *Landscape Urban Plann.* 107 (3): 307–316. https://doi.org/10.1016/j.landurbplan.2012.06.005.

Hankey, S., T. Lu, A. Mondschein, and R. Buehler. 2017. “Merging traffic monitoring and direct-demand modeling to assess spatial patterns of annual average daily bicycle and pedestrian traffic.” In *Transportation Research Board 2017 Annual Meeting*, 1–13. Washington, DC: Transportation Research Board.

Harkey, D., D. W. Reinfurt, M. Knuiman, J. R. Stewart, and A. Sorton. 1998. *Development of the bicycle compatibility index: A level of service concept—Final report*. Chapel Hill, NC: Univ. of North Carolina.

Hartanto, K. 2017. “Developing a bikeability index to enable the assessment of transit-oriented development (TOD) nodes.” Master’s thesis, Faculty of Geo-Information Science and Earth Observation, Univ. of Twente.

Hasani, M., A. Jahangiri, I. N. Sener, S. Munira, J. M. Owens, B. Appleyard, S. Ryan, S.M. Turner, and S. Ghanipoor Machiani. 2019. “Identifying high-risk intersections for walking and bicycling using multiple data sources in the city of San Diego.” *J. Adv. Transp.* 2019: 1–15. https://doi.org/10.1155/2019/9072358.

Hedman, C., D. Elliott, T. Srini, and S. Kooragayala. 2017. “Austin and the state of low-and middle-income housing.” Accessed April 19, 2020. https://www.urban.org/sites/default/files/publication/93781/austin_lmi_housing_0.pdf.

Howell, D. C. 1997. *Statistical methods for psychology*. 4th ed. Belmont, CA: Duxbury Press.

Jacobsen, P. L. 2015. “Safety in numbers: More walkers and bicyclists, safer walking and bicycling.” *Injury Prevention* 21 (4): 271–275. https://doi.org/10.1136/ip.9.3.205rep.

Jaffe, E. 2015. “The poor bike, the rich bike-share.” Accessed January 18, 2020. https://www.bloomberg.com/news/articles/2015-10-30/cycling-s-equity-gap-divides-low-income-bike-riders-and-high-income-bike-share-users.

Kang, H., D. H. Kim, and S. Yoo. 2019. “Attributes of perceived bikeability in a compact urban neighborhood based on qualitative multi-methods.” *Int. J. Environ. Res. Public Health* 16 (19): 3738. https://doi.org/10.3390/ijerph16193738.

Kim, N. S., and Y. O. Susilo. 2013. "Comparison of pedestrian trip generation models." *J. Adv. Transp.* 47 (4): 399–412. https://doi.org/10.1002/atr.166.

KLBJ. 2019. "City releases first safe routes to school infrastructure report." Accessed January 18, 2020. https://www.newsradioklbj.com/austinlocalnews/city-releases-first-safe-routes-to-school-infrastructure-report/.

Krenn, P. J., P. Oja, and S. Titze. 2015. "Development of a bikeability index to assess the bicycle-friendliness of urban environments." *Open J. Civ. Eng.* 5 (4): 451–459. https://doi.org/10.4236/ojce.2015.54045.

Krizek, K. J. 2003. "Operationalizing neighbourhood accessibility for land use–travel behavior research and regional modeling." *J. Plann. Educ. Res.* 22 (3): 270–287. https://doi.org/10.1177/0739456X02250315.

Le, H. T., R. Buehler, and S. Hankey. 2018. "Correlates of the built environment and active travel: Evidence from 20 US metropolitan areas." *Environ. Health Perspect.* 126 (7): 077011. https://doi.org/10.1289/EHP3389.

League of American Bicyclists. 2015. "New platinum, new gold bicycle friendly communities." Accessed January 18, 2020. https://www.bikeleague.org/content/new-platinum-new-gold-bicycle-friendly-communities.

League of American Bicyclists. 2017. "Where we ride: Analysis of bicycle commuting in American cities." Accessed January 18, 2020. https://bikeleague.org/sites/default/files/Where_We_Ride_2017_KM_0.pdf.

Lin, J. J., and Y. H. Wei. 2018. "Assessing area-wide bikeability: A grey analytic network process." *Transp. Res. Part A Policy Pract.* 113: 381–396. https://doi.org/10.1016/j.tra.2018.04.022.

Lindsay, G., A. Macmillan, and A. Woodward. 2011. "Moving urban trips from cars to bicycles: Impact on health and emissions." *Aust. N. Z. J. Public Health* 35 (1): 54–60. https:/doi.org/10.1111/j.1753-6405.2010.00621.x.

Lindsey, G. H. 2011. "Forecasting use of nonmotorized infrastructure: Models of bicycle and pedestrian traffic in Minneapolis, Minnesota." In *Transportation Research Board 90th Annual Meeting*, 1–16. Washington, DC: Transportation Research Board.

Liu, X., and J. Griswold. 2009. "Pedestrian volume modeling: A case study of San Francisco." *Yearbook Assoc. Pacific Coast Geogr.* 71 (1): 164–181. https://doi.org/10.1353/pcg.0.0030.

McNeil, N., J. Dill, D. DeVitis, R. Doubleday, A. Duncan, and L. Weigand. 2017. *Manual on pedestrian and bicycle connections to transit*. Rep. No. 0111. Washington, DC: Federal Transit Administration.

Mesa, V. G., and D. E. P. Barajas. 2013. "Calibikeability index map: A tool for evaluating public investment and future needs." *J. Transp. Geogr.* 4 (1): 5–8.

Miranda-Moreno, L., and D. Fernandes. 2011. "Modeling of pedestrian activity at signalized intersections: Land use, urban form, weather, and spatiotemporal patterns." *Transp. Res. Rec.* 2264: 74–82. https://doi.org/10.3141/2264-09.

Munira, S., and I. N. Sener. 2017. *Direct-demand modeling in estimating nonmotorized activity: A literature review*. Austin, TX: Texas A&M Transportation Institute.

National Center for Safe Routes to School. 2010. "Safe routes to school travel data: A look at baseline results from parent surveys and student travel tallies." Accessed January 18, 2020. http://www.saferoutesinfo.org/sites/default/files/SRTS_baseline_data_report.pdf.

National Center for Safe Routes to School. 2017. "Walking to school: Trends, issues and evidence." Accessed January 18, 2020. http://www.walkbiketoschool.org/wp-content/uploads/2017/01/Walking-to-school-research-1.pdf.

NCSA (National Center for Statistics and Analysis). 2019. *2018 fatal motor vehicle crashes: Overview*. Rep. No. DOT HS 812 826. Washington, DC: National Highway Traffic Safety Administration.

Nordback, K., W. E. Marshall, B. N. Janson, and E. Stolz. 2013. "Estimating annual average daily bicyclists: Error and accuracy." *Transp. Res. Rec.* 2339 (1): 90–97. https://doi.org/10.3141/2339-10.

Ortuzar, J. D. D., and L. G. Willumsen. 2011. *Modelling transport*. 4th ed. Chichester, UK: John Wiley & Sons.

Owen, N., E. Cerin, E. Leslie, L. du Toit, N. Coffee, L. D. Frank, A. E. Bauman, G. Hugo, B. E. Saelens, and J. F. Sallis. 2007. "Neighborhood walkability and the walking behavior of Australian adults." *Am. J. Preventive Med.* 33 (5): 387–395. https://doi.org/10.1016/j.amepre.2007.07.025.

Pulugurtha, S. S., and S. S. Repaka. 2008. "Assessment of models to measure pedestrian activity at signalized intersections." *Transp. Res. Rec.* 2073: 39–48. https://doi.org/10.3141/2073-05.

Pushkarev, B., and J. Zupan. 1971. "Pedestrian travel demand." *Transp. Res. Rec.* 377: 37–53.

Shaheen, S., and A. Cohen. 2019. *Shared micromobility policy toolkit: Docked and dockless bike and scooter sharing*. Richmond, CA: UC Berkeley Transportation Sustainability Research Center.

Song, M. K., F. C. Lin, S. E. Ward, and J. P. Fine. 2013. "Composite variables." *Nurs. Res.* 62 (1): 45–49. https://doi.org/10.1097/NNR.0b013e3182741948.

Stipdonk, H., and M. Reurings. 2012. "The effect on road safety of a modal shift from car to bicycle." *Traffic Inj. Prev.* 13 (4): 412–421. https://doi.org/10.1080/15389588.2012.660661.

Tabeshian, M., and L. Kattan. 2014. "Modeling nonmotorized travel demand at intersections in Calgary, Canada: Use of traffic counts and geographic information system data." *Transp. Res. Rec.* 2430 (1): 38–46. https://doi.org/10.3141/2430-05.

Turner, S., C. S. Shafer, and W. P. Stewart. 1997. *Bicycle suitability criteria for state roadways in Texas*. Austin, TX: Texas Dept. of Transportation.

Turner, S., et al. 2017. *Synthesis of methods for estimating pedestrian and bicyclist exposure to risk at areawide levels and on specific transportation facilities*. Washington, DC: DOT.

Van Dyck, D., G. Cardon, B. Deforche, N. Owen, J. F. Sallis, and I. De Bourdeaudhuij. 2010. "Neighborhood walkability and sedentary time in Belgian adults." *Am. J. Preventive Med.* 39 (1): 25–32. https://doi.org/10.1016/j.amepre.2010.03.004.

Van Dyck, D., E. Cerin, T. L. Conway, I. De Bourdeaudhuij, N. Owen, J. Kerr, G. Cardon, L. D. Frank, B. E. Saelens, and J. F. Sallis. 2012 "Perceived neighborhood environmental attributes associated with adults' transport-related walking and cycling: Findings from the USA, Australia and Belgium." *Int. J. Behav. Nutr. Phys. Act.* 9 (1): 70. https://doi.org/10.1186/1479-5868-9-70.

Vanwolleghem, G., S. D'Haese, D. Van Dyck, I. De Bourdeaudhuij, and G. Cardon. 2014. "Feasibility and effectiveness of drop-off spots to promote walking to school." *Int. J. Behav. Nutr. Phys. Act.* 11 (1): 136. https://doi.org/10.1186/s12966-014-0136-6.

Winters, M., M. Brauer, E. M. Setton, and K. Teschke. 2013. "Mapping bikeability: A spatial tool to support sustainable travel." *Environ. Plann. B: Plann. Des.* 40 (5): 865–883. https://doi.org/10.1068/b38185.

Winters, M., K. Teschke, M. Brauer, and D. Fuller. 2016. "Bike score®: Associations between urban bikeability and cycling behavior in 24 cities." *Int. J. Behav. Nutr. Phys. Act.* 13 (1): 18. https://doi.org/10.1186/s12966-016-0339-0.