Developing Crash Modification Factors for Separated Bicycle Lanes

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FOREWORD

In 2020, 938 bicycle roadway fatalities occurred in the United States. Transportation agencies are actively exploring alternative bicycle lane configurations that may further reduce the number of bicycle-related crashes on the road. The project titled *Developing Crash Modification Factors for Separated Bicycle Lanes* considered the safety effectiveness of separated bicycle lanes (SBLs), sometimes known as protected bicycle lanes, whereby the bicycle lane is separated from motor vehicle traffic with a spatial buffer or with a vertical barrier such as a flexible post (flexi-post).

The findings from this study supported the development of a crash modification factor (CMF) for converting a traditional bicycle lane to an SBL with flexible posts. The analysis also resulted in a CMF for SBLs that have a blended vertical element located in the buffer area. This report may be of interest to transportation practitioners, transportation safety researchers, industry representatives, and engineers and others working to improve transportation safety.

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16. Abstract
This project investigated how conversions of a traditional bicycle lane to a separated bicycle lane (SBL) influence the safety performance of the roadway. The study further assessed the role of the type of vertical element used in the SBL and its influence on safety performance based on a reduction in bicycle-related crashes. The study models included data from Cambridge, MA; San Francisco, CA; and Seattle, WA. Data from Austin, TX, and Denver, CO, were then used for model validation. The study produced exposure models and crash modification factors (CMFs) for Cambridge, San Francisco, and Seattle. The research summarizes the development of individual city models and a three-city composite model for CMFs. Assuming a baseline condition that uses a traditional bicycle lane and a countermeasure that upgrades the bicycle lane to an SBL, the resulting CMF values varied based on the type of vertical element. The resulting CMFs ranged from 0.28 to 0.60; however, the condition of converting a traditional bicycle lane to an SBL that uses flexible posts (known as flexible posts) had a rounded CMF value of 0.50. This outcome suggests that this SBL treatment can reduce crashes by 50 percent. The report provides additional CMFs for variations of the bicycle lane and the vertical elements. These CMFs had similar results. The findings from this study can be useful to an agency interested in reducing bicycle-related crashes.

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SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1,000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2,000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2,000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	2.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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LIST OF ABBREVIATIONS AND ACRONYMS

AADB	annual average daily bicycle (units: bicycles per day)
AADT	annual average daily traffic (units: vehicles per day)
AASHTO	American Association of State Highway and Transportation Officials
ADBT	average daily bicycle traffic
ADT	average daily traffic
AIC	Akaike information criterion
Bpd	bicycles per day
CMF	crash modification factor
CV	coefficient of variation
df	degrees of freedom
FHWA	Federal Highway Administration
flexi-post	flexible post
GLM	generalized linear model
Log	logarithm with a base of 10
LU	land use
MV	motor vehicle
NACTO	National Association of City Transportation Officials
NB	northbound
REML	restricted maximum likelihood
Pr	probability
PS	propensity score
PSW	propensity score weighting
SBL	separated bicycle lane
vpd	vehicles per day
WB	westbound

EXECUTIVE SUMMARY

During the first phase of this project, the research team evaluated whether enough constructed separated bicycle lanes (SBLs) existed to support a statistical safety-based analysis. Following this assessment and confirmation of the number of candidate sites, the research team scheduled data collection for spring 2020. Due to the pandemic, the data collection effort was limited to identification of preexisting databases and physical site assessments using aerial photos and an interactive panoramic street viewing application.

The objective of this study was to determine a crash modification factor (CMF) that estimates the safety effect of converting a traditional bicycle lane to an SBL. The SBL is characterized by a buffer with a vertical element located between the motor vehicle (MV) and bicycle lanes. The safety analysis is based on bicycle-related crashes.

DATABASE DEVELOPMENT

Due to travel restrictions in 2020, the research team developed a database that included information that could be compiled from existing bicycle count data, road characteristic information, and crash data available from the target jurisdictions. Locations that did not have these three critical features could not be included; however, the team allowed some variability for how much bicycle count data could be used and potentially extrapolated to surrounding facilities.

Study Sites

The team developed a second matching database that included street-level information, such as traffic operations (one-way versus two-way roads for bicycles and MVs), varying traffic control at bounding intersections, parking presence and type, and roadway cross section.

Based on the identified site requirements, the following candidate locations were identified:

- Austin, TX.
- Cambridge, MA.
- Denver, CO.
- San Francisco, CA.
- Seattle, WA.

Data for Austin and Denver were reserved for validation purposes. The analysis focused on Cambridge, San Francisco, and Seattle.

Exposure and CMF Models

Due to the limited number of bicycle counts, the team developed statistical models to estimate bicycle exposure at the sites included in the database that did not have available bicycle volumes. These exposure models were developed so that each of the three target cities could be independently assessed.

RESULTING CMFs

Following the exposure model development, the research team then developed CMFs that estimated the following scenarios:

- Converting traditional bicycle lanes to SBLs with flexible posts (flexible posts) (CMF = 0.50).
- Converting flush buffered bicycle lanes to SBLs with flexible posts (CMF = 0.44).
- Converting traditional or flush buffered bicycle lanes to SBLs with flexible posts (CMF = 0.47).
- Converting traditional bicycle lanes to SBLs with a blend of flexible posts and other vertical elements (CMF = 0.64).
- Converting flush buffered bicycle lanes to SBLs with a blend of flexible posts and other vertical elements (CMF = 0.57).
- Converting traditional or flush buffered bicycle lanes to SBLs with a blend of flexible posts and other vertical elements (CMF = 0.60).

Possibly, other bicycle crashes may have occurred and were not reported. The research team was unable to incorporate these unreported crashes into the scope of this study.

CHAPTER 1. INTRODUCTION

INTRODUCTION

In 2020, the United States experienced 938 bicycle fatalities due to roadway-related crashes.[1] This high number of bicycle-involved collisions emphasizes the need to place priority on analyzing and enhancing the safety of bicyclists. In recent years, transportation agencies have constructed a variety of bicycle lane configurations, including separated bicycle lanes (SBLs). An SBL is also sometimes referred to as a “protected bicycle lane.”

SBLs provide a bicycle lane that is separated from the adjacent motor vehicle (MV) lanes by both a buffer and a vertical element between the MV lanes and the bicycle lane. The SBL is a newer treatment, and the safety and operational effects of the SBLs are not fully known.

Project Objective

This report summarizes the development of crash modification factors (CMFs) based on SBLs for facilities in Cambridge, MA; San Francisco, CA; and Seattle, WA, and then tested for facilities in Austin, TX, and Denver, CO. Including bicycle exposure in safety assessments is necessary because the number of bicycles that use the roadway can be expected to directly contribute to the number of crashes that occur on that facility.

Study Approach

The annual average daily bicycle volume (AADB) is one of the most common terms used to represent bicycle exposure. Unfortunately, AADB is not a common variable that is widely collected, and locations where transportation agencies do acquire the AADB information may be limited to seasonal or short-term count values. Because the purpose of this study was to evaluate the safety performance of SBLs, the researchers needed to assess known bicycle count data and contrast those data with other site and road characteristics, with a goal of identifying surrogate variables that may be used to collectively estimate the bicycle count information for roadway facilities with similar characteristics. These models are known as exposure models (see chapters 4, 5, and 6 for additional information on the exposure models).

An initial stage of this project included data collection and analysis that would enable the research team to estimate bicycle exposure that could then be used in the development of CMFs. The way people traveled, worked, and used their bicycles for leisure and commuting purposes dramatically shifted in 2020 due to the COVID-19 pandemic. Initially, the data collection for this SBL project was to be based on field data to account for exposure; however, the research team had to modify the data sources for the project and target cities that did have some available bicycle counts. Instead of field visits, the research team used online mapping visual tools to document the road conditions for the database on this project. (See chapter 3 for additional information regarding the data collection and database development.) Data from 2020 or later were excluded from this study because of the altered usage pattern that occurred due to the COVID-19 outbreak.

This report begins with chapter 1 (this chapter), which introduces the project purpose. Chapter 2 then summarizes published literature regarding known safety performance of bicycle facilities with a focus on SBLs. Chapter 3 provides a brief overview of the data collection process used for this analysis. Chapters 4, 5, and 6 review exposure model estimation for Cambridge, San Francisco, and Seattle, respectively. Chapter 7 then summarizes the estimation efforts for developing CMFs for SBLs. The body of the report concludes with conclusions in chapter 8, appendixes, and references.

CHAPTER 2. LITERATURE REVIEW

The construction of various lane configurations that accommodate bicycles along an urban collector or arterial can help to remove cyclists from sidewalks or from travel lanes where the bicycles must share the lane with MVs. Bicycle lanes, as an example, can reduce conflicts between pedestrians and bicyclists (for sidewalk locations) and between MVs and bicycles (for shared travel lane scenarios at nonintersection locations). The bicycles and MVs, however, must still interact at intersection locations.

Intuitively, providing a dedicated bicycle lane should result in fewer and less severe bicycle-related crashes, yet the research related to bicycle lanes provides mixed results.[(1,2)] The inclusion of a buffer between the MV lane and the bicycle lane provides additional lateral separation between the bicycle and adjacent MVs. Enhancing this design by introducing a vertical element that physically separates the bicycles and the MVs and converts the bicycle facility to an SBL further improves cyclist comfort.

Recently, two studies specifically focused on bicycle lane performance. The report, *Recommended Bicycle Lane Widths for Various Roadway Characteristics* (NCHRP Report 766), provides guidance on recommended bicycle lane widths and associated roadway characteristics.[(1)] The authors of that report noted that a buffered lane provides advantages over a standard or a wide bicycle lane. The Federal Highway Administration (FHWA) further evaluated the safety performance of existing SBLs in appendix C of its *Separated Bicycle Lane Planning and Design Guide*.[(3)] The authors noted, however, that the inconsistent nature of the available data—in particular, bicycle volume data—created difficult analysis issues for SBL facilities where exposure is a key element related to these facilities' overall safety.

Many additional factors can contribute to the safety effects of bicycle lanes, including the following examples:

- The corridor speed limit.
- The frequency of driveways.
- The lateral placement of roadside objects.
- The buffer separation between vehicle lanes and the bicycle lane.
- The number and width of neighboring lanes.
- The width of the actual bicycle lane.
- The number and type of intersections.
- The volume of MVs (passenger cars and trucks), bicycles, and pedestrians.
- The fact that the construction of a bicycle facility is likely to attract more cyclists to the corridor location.

The role of the corridor as part of a larger street network must also be considered to capture the context of a facility, including items such as bicycle route alternatives, facility connectivity, and operational consistency.

The following section provides brief definitions of bicycle lanes and SBLs and then further defines the objective that was the focus of this study.

DEFINITIONS AND COMMON TERMS

The distinction between a bicycle lane, a bikeway, and an SBL facility merits clarification. This section defines these facilities and, in doing so, highlights why the SBL is uniquely different than other bicycle facilities.

Bicycle Lane

The use of bicycle lanes in the United States dates back several decades. The 2012 American Association of State Highway and Transportation Officials (AASHTO) *Guide for the Development of Bicycle Facilities*, fourth edition, defines a bicycle lane as:

> A portion of roadway that has been designated for preferential or exclusive use by bicyclists by pavement markings and, if used, signs. The roadway portion is intended for one-way travel, usually in the same direction as the adjacent traffic lane, unless designed as a contraflow lane.(4)

Bikeway

AASHTO's 2012 guide further defines a bikeway as:

> A generic term for any road, street, path, or way which in some manner is specifically designated for bicycle travel, regardless of whether such facilities are designated for the exclusive use of bicycles or are to be shared with other transportation modes.(4)

Separated Bicycle Lane

The SBL is also often referred to as a "cycle track" or a "protected bikeway" or "bicycle lane." A simple description by Bicycle East Bay in Oakland, CA, refers to SBL facilities as sidewalks for bicycles.(5) The unique characteristics of this facility include lateral physical separation or protection of the bicycle lane from the adjacent MV lanes. The physical separation of an SBL is accomplished with a vertical element that may include a variety of applications such as consistently spaced flexible posts (flexible posts) that do not fully limit access. The physical separation could also restrict adjacent MV access with continuous longitudinal barriers.

The SBL may be one-way or two-way and can be positioned on the left or right side of roadways that are also one-way or two-way; however, the most common applications tend to locate the SBL on the right side of the road in the direction of travel (figure 1).

Source: FHWA.

Figure 1. Photo. SBLs for both directions of travel.

AASHTO's 2012 guide does not include an SBL as a recommended bicycle facility, but this type of design option is addressed in recent documents by FHWA and the National Association of City Transportation Officials (NACTO).(3,6)

The 2015 FHWA *Separated Bicycle Lane Planning and Design Guide* defines an SBL as:

> An exclusive facility for bicyclists that is located within or directly adjacent to the roadway and that is physically separated from motor vehicle traffic with a vertical element. Separated bicycle lanes are differentiated from standard and buffered bicycle lanes by the vertical element.(3)

The 2012 NACTO *Urban Bikeway Design Guide* uses the term *cycle track* and defines it as:

> A cycle track is an exclusive bicycle facility that combines the user experience of a separated path with the on-street infrastructure of a conventional bicycle lane. A cycle track is physically separated from motor traffic and distinct from the sidewalk.(6)

A key component that distinguishes the SBL from other bicycle facilities is the use of a physical separation that includes some type of vertical element. This vertical element is one of several factors that should be considered when assessing the safety performance of an SBL facility.

SBL CHARACTERISTICS TO CONSIDER

This literature review focused on the safety aspects of SBLs located in North America. The section that reviews SBL characteristics to consider includes a summary of the varying SBL features. This review also includes a review of the known safety effects of the SBLs.

The implementation of an SBL can include several elements that collectively contribute to the safety performance of a facility. The following factors should be deliberated when considering deployment of SBLs to a specific facility:

- Unique geometric configurations.
- Directional considerations and associated dimensions.
- Vertical elements.
- Contextual applications.
- Intersection-specific issues.
- Segment (nonintersection)-specific issues.

Unique Geometric Configurations

The unique design of urban arterial and collector corridors, where SBLs are most often located, must be carefully balanced with the adjacent land use. Many of these corridors include attractors that increase the likelihood of commuting and recreational cyclists. These locations require specific assessments on how to accommodate vulnerable road users while maintaining the appropriate level of corridor operations.

Directional Considerations and Associated Dimensions

For SBL facilities, the bicycle lane may be one-way or two-way, depending on the demands of the facility, though the use of contraflow bicycle lanes is generally discouraged for two-way streets. The use of contraflow bicycle lanes at streets with one-way MV activity may be acceptable in the following situations:

- The contraflow bicycle lane helps substantially reduce out-of-direction travel.

- Wrong-way bicycle activity exists at the facility, and the contraflow bicycle lane will accommodate these bicycles.

- The contraflow lane provides access to a high-use destination property.

- The number of intersecting streets, alleys, or driveways is limited.

- The contraflow lane bicycle entrance and exit are safe and convenient.[7]

In addition to the one-way or two-way SBL facilities or MV lanes, the design must also consider the lateral placement of the SBLs. The width of the road cross section and available space for the SBL buffer are also critical elements of the design.

In addition, any characteristics that are critical for traditional bicycle lanes will generally be of concern for SBL applications. For example, extreme vertical grades will often require bicycle lane width adjustments.[1,3] If a continuous facility that does not permit same-direction passing is constructed, the managing transportation agency can expect to observe reduced compliance that will likely affect safety.

Table 1 summarizes common SBL directional configurations, companion bicycle lane and buffer width recommendations, and additional considerations that should be included when assessing the selection and placement of SBL configurations. As noted in this table, many of the options will further complicate bicycle, pedestrian, and MV interactions at intersection locations. The values shown in table 1 are as cited in the noted references; however, each agency may use widths that vary from those shown.

Table 1. Recommended SBL directions and dimensions.[2,5]

SBL Type	MV Lanes	Lateral Placement	Bicycle Lane Width (ft)	Buffer Width (ft)	Additional Considerations
One-way	One-way	• Generally right-side conditions (preferred)* • Left side (under unique circumstances)	7 preferred 5 minimum	3 minimum	Avoid using minimum bicycle lane width where same-direction bicycle passing is expected
One-way	Two-way	Both sides (left and right)	7 preferred 5 minimum	3 minimum	Avoid using minimum bicycle lane width where same-direction bicycle passing is expected
One-way	Two-way	Central median	Varies based on median configuration	Varies based on median configuration	Fewer turning conflicts but creates challenges at intersections
Two-way	One-way	Right side typical*	12	Varies	Creates challenges at intersections
Two-way	Two-way	Right side typical*	12	Varies	Fewer turning conflicts but creates challenges at intersections; used if space cannot be achieved to accommodate separate SBLs on each side

*Left-side SBL applications are considered when:[3,6]

- Route has high transit demand.
- Left side has fewer access points than right side.
- Land use on left side is more likely cyclist destination.
- Right side of road has on-street parking.

Vertical Elements

A wide variety of potential vertical elements may be used to separate the bicycle lane from adjacent MV lanes and sidewalks. Table 2 summarizes several of the vertical elements observed in the published literature.[2,5,7] Many of the potential vertical elements can be generally separated into a continuous treatment category, whereby the bicycle traffic is distinctly separated from the adjacent MV or pedestrian traffic for the length of the nonintersection SBL section. As an alternative, several less rigid or flexible vertical elements enable periodic gaps in the physical separation. Though the continuous vertical element may generally be preferred, there may also be a need to blend these two treatment types at locations where some access must be maintained for other road users.

Table 2. Example SBL vertical elements to consider.

Vertical Element	Source
On-street parking (24-h posted)	Continuous at nonintersection locations[6,8]
Raised curb or median	Continuous at nonintersection locations[6,8]
Concrete barriers	Continuous at nonintersection locations[3]
Raised lane	Continuous at nonintersection locations[3]
Landscaped buffers	Continuous at nonintersection locations[8]
Tubular markers (bollards) or flexible posts	Flexible with limited gaps in vertical elements at nonintersection locations[6]
Planters	Flexible with limited gaps in vertical elements at nonintersection locations[3,6]
Parking stops	Flexible with limited gaps in vertical elements at nonintersection locations[3]
Combination of treatments	Blended vertical treatments[3]

Contextual Applications—Transit and Pedestrian Considerations

As indicated in table 1, the placement and orientation of SBL facilities are often influenced by corridor user demands. Transit operations and supporting facilities and pedestrian demand are two contextually specific characteristics that are likely to occur at urban roadways where SBL facilities are also considered.

In addition to increased bus volumes along an urban corridor, the location of transit lanes, bus stops, or transit stations can directly influence the recommended placement of SBL facilities. As noted in table 1, left-side placement of an SBL may be appropriate if the corridor has high transit demand and uses the right side of the road to conduct transit operations.[6] In many locations, the SBL is located to the right of active bus lanes or parking lanes. This type of configuration requires a pedestrian to cross the SBL to access the bus or parked vehicles.

Some agencies prohibit the placement of bicycle lanes between the curb and a parking lane. For example, the Wisconsin Department of Transportation does not allow this configuration and notes that these bicycle lane configurations restrict visibility for both the drivers of MVs and bicyclists at intersection or driveway locations.[7]

Intersection-Specific Issues

The transition from a nonintersection SBL location to an intersection configuration presents many challenges. This location requires some level of interaction between all road users and can introduce confusing configurations that road users do not always interpret correctly.

Monsere et al. defined SBL intersection configurations as three categories.[1]

- Mixing zones where bicycles and turning vehicles are required to share the same space.
- Turning zones where the through bicycle maneuver is shifted away from the curb and located to the left or right of turning MVs.
- Signalization where bicycles and turning MVs receive separate signalized movements.

Following execution of a series of surveys for study sites at five locations, Monsere et al. (determined that the mixing zones are more readily understood by cyclists and drivers.[(9)] Researchers at Portland State University in Oregon extended their research by evaluating user "comfort" curves to assess suitable intersection configurations.[(9)] That study focused on the mixing and turning zone configurations. The goal of the Portland State University research effort was to determine design recommendations based on the comfort levels of the bicyclists and their interaction with other road users.[(10)] Rather than assessing crash data, the study used a combination of video, surveys, and microsimulation activities. Due to the available study sites, the research primarily focused on one-way configurations and right-turn maneuver interactions.

Segment (Nonintersection)-Specific Issues

In addition to the transit issues previously noted, SBL nonintersection operations are more straightforward than their intersection counterparts. Locations where midblock access points are permitted, however, can compromise SBL operations, introduce conflicts, and create visibility issues. At locations where on-street parking is permitted, the parking should be limited to immediately upstream and downstream of the access point to enhance sight distance. In addition, signage should clearly indicate to road users that the SBL operations have priority over driveway operations.[(3)]

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[1]Monsere, C. 2017. "Contextual Guidance at Intersections for Protected Bicycle Lanes." NACTO C4C Conference Call presentation, unpublished.

Summary of Key Variables to Consider

A variety of issues need to be considered when assessing the safety of an SBL facility. Table 3 summarizes these potential elements.

Table 3. SBL variables to consider.

Data Need	Potential Elements
Crash data	• Total number of crashes. • Number of fatal and injury crashes (specific consideration to who is injured: MV drivers or passengers, bicyclists, or pedestrians).
Exposure	• ADT or peak-hour volumes for MVs (passenger cars and trucks), bicycles, and pedestrians. • Land use and driveway types (as potential volume surrogates). • The increase in bicyclists due to the placement of SBL facilities is also an important exposure consideration.
Year of construction	SBLs constructed earlier than 2010 may not be suitable if exposure information and crash data are not available.
Width of buffer	Locations with on-street parking should be further assessed to determine actual and effective buffer widths.
Vertical element	• Flexible posts, bollards, and light poles. • Curb or raised median. • Landscaping and planters. • Concrete (zebra/armadillo) bumps, buttons, and parking stops. • Parked cars. • Grade. • Concrete barrier, guardrail, and fence.
Length (miles)	Primarily for nonintersection SBL assessment.
Intersection channelization and traffic control	• Primarily for intersection SBL assessment. • Islands (traditional, bend-in, bend-out, turn lanes, etc.). • MV and bicycle signalization. • Signage and pavement markings.
Lighting	Street light presence, placement, and type
Corridor information	• Speed limit. • Driveway density. • Number, type, and width of lanes. • Number and type of intersections. • Street network configuration. • Vehicle parking restriction hours.

Data Need	Potential Elements
Roadway facility type	• Urban arterial (two-way and one-way). • Urban collector (two-way and one-way). • Urban local street (two-way and one-way).
SBL facility configuration	• Right side, one-way or two-way. • Left side, one-way or two-way. • Middle, two-way.
Unique SBL features	• Truck aprons. • Mixing zones or elevated SBLs at driveways/crossings. • Green markings. • Bicycle facility continuity and operational consistency.

ADT = average daily traffic.

KNOWN SAFETY EFFECTS OF SBLS

Within the last decade, many U.S. transportation agencies have implemented SBLs in urban regions to help promote the bicycle as a viable transportation option. Though empirical safety data analysis related to SBLs in the United States continues to evolve, the widespread European application and safety evaluation of these facilities have suggested several potential safety benefits that are identified in guidance documents by FHWA and NACTO. This section summarizes these expected safety benefits, describes the North American safety studies that have occurred in recent years in greater detail, reviews the study design and analysis methods used for these studies, and then summarizes these findings.

Safety Benefits

In 2015, FHWA published a guidance document entitled *Separated Bicycle Lane Planning and Design Guide.*(3) This document specifically notes the following four expected safety benefits of implementing an SBL:

- Physical separation will reduce crash frequency and severity while also increasing cyclist comfort.

- Additional protection helps to promote use by providing peace of mind to novice cyclists.

- Strategic applications of SBLs can be integrated into the bicycle network at locations with the greatest need.

- Designs can help enhance pedestrian safety by shortening crossing distances and accommodating additional pedestrian refuge at crossing locations.

NACTO's *Urban Bikeway Design Guide* refers to SBLs as "cycle tracks" and further identifies the following safety benefits:

- Provides protected, dedicated space for cyclists.
- Reduces cyclist fear of overtaking vehicles.
- When contrasted to traditional bicycle lanes, minimizes safety concerns related to "dooring" where cyclists are struck by the opening doors of parked cars.(6)

These identified safety benefits are intuitive, but confirming that these benefits apply to SBL applications in the United States is necessary. The North American safety research is summarized in the following section.

Related Safety Research

Because the number of SBL locations in the United States has been limited, much of the published literature related to the safety effect of these facilities has focused on northern Europe, where bicycle facilities of this type have existed for many years. Many of the European facilities are not located on multilane roadways and, therefore, have different contextual configurations than the U.S. and Canadian SBL applications. This difference suggests that the use of crash information from other countries may be informative but not directly applicable to the United States. A 2013 paper by Thomas and DeRobertis reviews the literature associated with urban SBLs.(11) The authors identified 23 papers that extended as far back as 1987 and noted that 22 of the papers were based on European facilities. Thomas and DeRobertis did compile the following general findings that may help transportation professionals in the United States determine key safety-related issues to consider:

- One-way SBLs tend to be safer than two-way SBLs.
- Constructing SBLs reduces the number of collisions and injuries.

A 2011 study by Lusk et al. examined six SBL locations in Montreal, QB, Canada, and contrasted each location with up to two reference streets where bicycle facilities were not present.(12) The original intent of the study was to focus on one-way and two-way SBL facilities, but the researchers determined that all the Montreal locations available to study were two-way, and, therefore, they ultimately focused on this configuration. Lusk et al. determined the crash rate for the SBLs to be 10.5 crashes per million bicycle-km. They also found the associated injury crash rate to be 8.5 injuries per million bicycle-km. The authors cautioned that the small sample size of six locations limited opportunities to determine unique factors that contributed to safety performance. The study corridors included entire SBL segments and did not separate intersection versus nonintersection crashes. Lusk et al. concluded that two-way SBL facilities appear to reduce or maintain crash and injury rates compared to streets without similar facilities.

In 2013 study, Lusk et al. evaluated 19 SBL facilities in the United States.(13) The researchers assessed crash data that extended from 0.3 yr to 8.6 yr. At some locations, exposure information was not available, so the researchers estimated the average daily bicycle count. The 19 study locations included sites in California, Colorado, Florida, Massachusetts, Minnesota, New York, Oregon, and Vermont. The physical characteristics—such as, one-way versus two-way, one side versus two sides, and type of physical separation—varied. Study corridor lengths varied from 0.16 km to 4.83 km. The researchers evaluated 55 crashes between MVs and bicycles. The study resulted in a crash rate of 2.3 crashes per million bicycle-km. The authors noted that some potential limitations of the study included the limited amount of available crash data associated with SBL facilities and a need to estimate or adjust bicycle counts for consistent periods.

Another 2013 study evaluated bicycling injury patterns in the Canadian cities of Vancouver, BC, and Toronto, ON.(14) For this study, the researchers used a case crossover design whereby the experimental design used injured cyclists as their own controls. The researchers recruited 690 study participants from local hospitals where they reported bicycle-related crash injuries. Of the associated crashes, 201 occurred at intersection locations, and 478 occurred at nonintersection locations. Though the research team evaluated a wide variety of road configurations and associated elements, they concluded that features that separate cyclists from MVs and pedestrians are associated with substantially lower-risk bicycle crashes.

In a 2013 study, Goodno et al. evaluated innovative bicycle facilities in Washington, DC.(15) As part of this study, the researchers evaluated an SBL facility on 15th Street by examining before–after crash data and conducting 6-h conflict studies at intersection locations. At the time of the study, only 10–14 mo of after crash data were available, so the authors could not draw definitive conclusions but did provide some observations. The number of crashes that involved bicycles increased after the SBL configuration was implemented. The authors noted, however, that approximately 40 percent of the cyclists were observed to disobey traffic signals, with many of them running the red lights. The researchers further noted that the local jurisdiction continues to monitor the crash trends at these locations and recommended adding bicycle traffic signal heads to help clarify cyclist expectations at these locations.

Three studies evaluated perceived and observed SBL safety.(15–16) The researchers did not have sufficient crash data to assess before and after conditions, so they used user survey data from 144 h of video (consisting of 12,900 bicycles) to assess cyclists' behavior at the SBL intersection study locations in Austin; Chicago, IL; Portland; San Francisco; and Washington, DC.(15,16) Most of cyclists indicated that the SBL installation resulted in a facility that felt safer. The MV drivers in the study areas provided mixed feedback, with only 37 percent indicating a perception of increased safety and 30 percent suggesting there was no perceived change to safety along the corridors. Pedestrians similarly provided mixed responses, with 33 percent suggesting an increase in safety and 48 percent suggesting no safety change. For the observed safety assessment, the researchers did not observe any collisions or near collisions during the period for which they acquired video data. The researchers did observe six minor conflicts, five of which occurred at the turning and mixing zones of the intersections.

In 2014, the New York City Department of Transportation evaluated SBLs constructed on Manhattan streets.(17) Although the before conditions varied across the sites, the New York City transportation officials concluded that the SBLs improved safety based on comparisons before and after at each site. General findings from this study relative to safety are as follows:

- A reduction in injury crashes (by 17 percent).
- A decrease in pedestrian injuries (by 22 percent).

- A decrease in cyclist injuries that occurred while bicycle volumes increased.
- A reduction in cyclists' risk for serious injury (by 75 percent) from 2001 to 2013.

In 2015, FHWA developed a planning and design guide for SBL facilities.(3) As part of this effort, the study noted limitations in existing U.S. SBL research and provided recommendations for future research efforts. For safety activities, the report recommended that as the number of SBL facilities increases, researchers should develop CMFs that consider the varying SBL configurations. The report further notes a need to improve crash-reporting practices, incorporate conflict analysis into the overall assessment, and expand the safety analyses based on design elements and intersection characteristics. Based on an assessment of data for several study locations, the report further notes a need to collect or improve the estimation of bicycle volume at study locations so that exposure can be directly considered in the safety assessment process.

Rothenberg, Goodman, and Sundstrom documented the crash analysis from the 2015 FHWA study.(3,18) They emphasized that safety assessments for SBL facilities should consider changes in total crashes (all crashes, including bicycle crashes) as well as changes due to the addition of these facilities. The researchers also noted that the following treatments appear to influence overall corridor safety:(18)

- The use of parking lanes in combination with other treatments resulted in fewer total crashes.

- A concrete curb (by itself and combined with other treatments) reduced the total number of crashes. However, the authors cautioned that only 14 of their 19 study sites included this treatment.

- Plastic bollards combined with other treatments reduced total crashes; however, plastic bollards as the only vertical element were associated with an increase in total crashes.

- Mixing zones combined with other treatments reduced total crashes (observed at five of six sites).

- Lateral shift at intersections contributed to fewer crashes, except when combined with other treatments (when total crashes appear to increase).

In a 2016 study, Zangenehpour et al. evaluated the safety of signalized intersections for locations in Montreal, PQ, Canada.(19) In this study, the research team used video data based on post encroachment time to evaluate cyclist behavior at 23 intersections (eight locations without an SBL, eight sites with the SBL on the right side, and seven locations with the SBL on the left side). This surrogate post encroachment value represents the time between when a cyclist departs a location and the potential time of collision with an MV. This metric is represented by the intersection of the two trajectories. Based on video reduction and analysis followed by a statistical assessment, the researchers provided the following observations:

- Intersections with SBLs also experienced a higher bicycle volume than locations where SBLs were not present (possibly suggesting cyclists prefer these facilities).

- The average bicycle speed appeared to be similar between all facilities.

- The number of interactions was greater at intersections with SBLs, but when exposure was considered, the rate of these interactions appeared to be lower for intersections with SBLs.

- Intersection approaches with SBLs on the right or left were safer than intersections that did not have SBLs.

- The likelihood of a dangerous interaction increased as the MV turning volume increased and decreased as the approaching bicycle volume increased.

Safety Assessment Methods

The existing SBL research has generally used the following three analytical approaches:

- Crash analysis.
- Video analysis (for conflicts and user compliance assessment).
- User surveys.

For each of these safety assessment methods, the researchers applied robust statistical techniques, where possible. The following summaries briefly describe how the researchers approached these analysis techniques.

Crash Analysis

Where practical, most of the published North American research has explored the use of crash analysis to assess, where feasible, before and after crash conditions. (See references 3, 9, 12, 13, 15, and 18.) This before–after approach included simple comparisons that do not directly consider changes in exposure up to and including robust assessments that incorporated comparison sites. In all cases, the greatest limitation to this approach appeared to be the limited availability of after crash data. This constraint resulted in small sample sizes or evaluations of very short periods after SBL implementation.

In general, a significant demand for determining the safety of SBL facilities in the United States exists. To date, traditional crash analysis research related to SBL configurations has been limited because after crash data are not always available, and optimal sample sizes that enable direct evaluations of the various SBL characteristics are therefore hard to obtain. The North American SBL literature draws attention to the need to better understand the influence of some unique SBL characteristics and to identify and populate missing data that, if available, could help enhance the transportation profession's understanding of SBL applications. Table 4 identifies the issues highlighted in the published literature and summarizes key elements that need to be determined as part of a comprehensive SBL safety assessment.

Table 4. SBL detailed site characteristics and data limitations.

Type of Issues	Issues
Detailed site characteristics noted in safety literature.	• Intersection versus nonintersection locations/crashes. • Type of vertical element separating traffic. • One-way versus two-way SBL facilities. • One-way versus two-way MV lanes. • SBL position (right side, left side, or other). • Site geometry (vertical grade, etc.). • Placement of bicycle traffic control devices. • Intersection transition types (turning zones, mixing zones, or separated).
Data limitations that contribute to expected safety performance.	• Law enforcement and user compliance. • Changes in cyclist route choice after SBL implementation. • Limited before or after site and crash data. • Unavailable bicycle volume information. • MV traffic volume, including turning volumes.

Video Analysis

Researchers used video data to evaluate actual user performance and conducted conflict studies to assess expected safety performance at each SBL location. (See references 9, 10, and 19.) This approach generally focused on two methods:

- Conflict analysis.
- Cyclist compliance and perceived understanding and adherence to traffic control and geometric configurations.

A secondary benefit of the video analysis was the ability to confirm bicycle volumes at each facility.

User Surveys

The strategic application of user surveys served as an additional safety assessment method. Researchers deployed surveys through a variety of techniques. One Canadian study used hospital records as a recruitment strategy.[14] Two studies deployed surveys by distributing them at the study sites and mailing them to residences near the SBL applications.[10,15,16]

LITERATURE REVIEW CLOSING COMMENTS

The published literature and evolving use of SBL treatments clearly indicate that this unique bicycle facility holds promise for enhanced safety along a corridor. Because the deployment of SBL facilities has been limited, finding sufficient after data at a site to conduct a meaningful evaluation can be challenging. Over time, as these SBL configurations are refined and implemented in the United States and Canada, this limitation will subside.

CHAPTER 3. DATA COLLECTION AND DATABASE DEVELOPMENT

This chapter reviews the data collection and database development. Initially, the team proposed to select one or two cities and conduct physical bicycle counts that could be used for exposure estimates. The data collection effort was scheduled for spring 2020, but the research team's efforts were curtailed because the pandemic began at the same time. Therefore, the researchers developed an alternative data collection approach that culminated with the development of a five-jurisdiction dataset.

SITE IDENTIFICATION

The literature review included an extended list of sites that might have SBL configurations. The team also used the Green Lane Project database as an additional source of information for identifying these sites (see reference 20 for more information on this study).

During earlier SBL studies, the researchers were challenged to identify enough locations with SBL implementation that would support a statistical assessment of study sites. Between 2010 and 2020, several transportation agencies implemented numerous additional SBL implementations. As a result, the research team for this project determined that the prospective sample size for an SBL study was sufficient to conduct a statistical assessment of the safety performance at SBL sites.

Site information included in the Green Lanes database was input by cyclists on a voluntary basis. Though there appeared to be some confusion about bicycle facility names (i.e., often a buffer bicycle lane was coded as an SBL), the Green Lanes database provided a rich resource for all types of bicycle facilities.[20] Most importantly, the street name, city, and State for this study's data were accessed from the Green Lanes database. The researchers used the city and State information in the Green Lanes database as well as supplemental data, such as crash data from local agencies, to select the following cities to include in this study:

- Cambridge.
- San Francisco.
- Seattle.

In addition, the research team selected two additional cities to test the validity of the CMFs ultimately developed for this study:

- Austin.
- Denver.

Within each city, several potential bicycle facilities may be present. Information about the data collection variables is addressed in the following data collection section.

DATA COLLECTION

The team compiled a list of data-related issues to consider when assessing the safety of an SBL facility. Table 5 identifies and defines these data requirements. To develop a CMF, there must be a base condition (e.g., no bicycle lane or standard bicycle lane) and a target CMF (e.g., buffered bicycle lane or SBL). For this reason, site selection included all bicycle facilities within the study region. The project team also included variables that could potentially influence the safety performance of SBL facilities as well as the bicycle exposure estimate. This supplemental information provided valuable insight into the operational characteristics of the facilities.

Table 5. Site information in database.

Data Need	Type of Data	Collected Site Data Elements
Location description	Location	• Street name • City • State • Beginning and ending cross streets
Starting latitude/longitude	Location	Measured to extended curb if at intersection
Ending latitude/longitude	Location	Measured to extended curb if at intersection
Length	Location	Distance in miles
Cross streets	Location	Between beginning and ending points
Number of MV lanes	Site characteristics	Total for both directions of travel
Roadway facility type	Site characteristics	• Urban arterial (two-way and one-way) • Urban collector (two-way and one-way) • Urban local street (two-way and one-way)
Intersection channelization and traffic control	Site characteristics	• Islands (traditional, bend-in, bend-out, turn lanes, etc.) • MV and bicycle signalization • Signage and pavement markings
Lighting	Site characteristics	Street light presence, placement, and type
Corridor information	Site characteristics	• Speed limit • Driveway density • Number, type, and width of lanes • Number and type of intersections • Street network configuration • Vehicle parking restriction hours • Presence and location of sidewalks
Direction of bicycle traffic flow	Site characteristics	Approaching or departing field of view
Traffic operations for MV lanes	Site characteristics	One-way or two-way

Data Need	Type of Data	Collected Site Data Elements
Median	Site characteristics	Physical separation of opposing MV maneuvers
Parking lane location	Site characteristics	Presence and location of parking lane located left and/or right side of road if applicable.
Type of bicycle facility	Bicycle facility characteristics	• No dedicated lane. • Traditional bicycle lane. • Buffered bicycle lane. • SBL.
Year of construction	Bicycle facility characteristics	SBLs constructed earlier than 2010 may not be suitable if exposure information and crash data are not available
Width of buffer	Bicycle facility characteristics	Locations with on-street parking should be further assessed to determine actual and effective buffer widths.
Vertical element	Bicycle facility characteristics	• Flexible posts, bollards, or light poles. • Curb or raised median. • Landscaping and planters. • Concrete (zebra/armadillo) bumps, buttons, and parking stops. • Parked cars. • Grade. • Concrete barrier. • Guardrail. • Fence.
SBL facility configuration	Bicycle facility characteristics	• Right side, one-way or two-way. • Left side, one-way or two-way. • Middle, two-way.
Unique SBL features	Bicycle facility characteristics	• Truck aprons. • Mixing zones. • Elevated SBLs at driveways/crossings. • Green markings. • Bicycle facility continuity and operational consistency.
Crash data	Supplemental data from agency where sites are located	Total number of crashes and number of fatal and injury crashes (specific consideration to who is injured: MV drivers or passengers, bicyclists, and pedestrians).

Data Need	Type of Data	Collected Site Data Elements
Exposure	Supplemental data from agency where sites are located	• ADT or peak-hour volumes for MVs (passenger cars and trucks), bicycles, and pedestrians). • Land use and driveway types (as potential volume surrogates). • Increase in bicyclists due to the SBL placement.

DATABASE DEVELOPMENT

Team members acquired crash data and road characteristic information from local agencies for each study site. After inspecting this information, however, the researchers determined that more site-specific data would be required. To develop a robust dataset, the team used a combination of aerial photographs, primarily available at an online mapping website, and then catalogued the site features for each region of interest. The primary tool for this effort was the interactive panoramic street viewing feature of the online mapping site. A team member virtually navigated each road in the study region and documented the site features. This virtual navigation enabled the researcher to document sites with no bicycle lanes, sites with traditional bicycle lanes, SBLs, and other types of sites. Ultimately, locations with a shared-use path or a sharrow were excluded from additional analyses. At the completion of this database development effort, the team had compiled data for five jurisdictions where bicycle facilities were common. These data were then used for the subsequent analysis phases of this project. Chapters 4, 5, and 6 provide additional database information about select study sites.

CHAPTER 4. ESTIMATING BICYCLE EXPOSURE: CAMBRIDGE

INTRODUCTION

This chapter reviews the estimation of bicycle exposure for Cambridge, first by assessing statistical relationships and models and, ultimately, by developing adjustment factors for the Cambridge study area. The City of Cambridge collects short-term traffic counts that can be used for this type of analysis. Cambridge has installed one permanent bicycle counter and conducts short-term counts at multiple locations regularly. The research team used these count data and blended these data with additional site features collected by the research team. The goal of this data-merging effort was to develop regression models that could reliably predict bicycle count data for typical urban roadway facilities. This chapter reviews this effort, first by identifying the data collection and database development effort and then by reviewing the subsequent modeling process.

DATA COLLECTION: AVAILABLE BICYCLE AND SITE DATA

The City of Cambridge has been consistently collecting bicycle count data for 16 intersections since 2003.(21) This effort includes bicycle count data for every year from 2003 to 2006 and for every other year since 2008. Due to the adverse weather in 2018, the city collected data in 2019 as well. The counts are typically collected for morning (AM) (7:30–9:15) and evening (PM) (4:30–6:45) peaks during weekdays in September. Additionally, in 2015, the city installed a permanent bicycle counter on Broadway in Kendall Square.(22)

The research team retrieved the original data from online sources and then used the Cambridge data to develop bicycle surrogate models. The data cover AM and PM peaks and provide the following information:

- Count location: the intersection at which the count was conducted.
- Year: the year of the count.
- Date: the date of the count.
- Time period: AM or PM count data.
- Time: the 15-min time interval of the data collection.
- Street: the name of particular streets for the counts at each intersection.
- Traffic direction: the direction of traffic.
- Cyclist location: where the cyclists were riding, on a street, sidewalk, or bicycle path. All the bicycle path data were removed from further analysis since the purpose of this study was evaluating the safety of various bicycle paths adjacent to MV roadways.
- Cyclist direction: the direction of bicyclists, with or against traffic or on a bicycle path.

- Movement type: how the bicyclists were moving through the intersection.
- Count: the counts of bicyclists.
- Temperature: the temperature when collecting data.
- Weather: the weather condition while collecting data.
- Latitude: the latitude of the conducted count.
- Longitude: the longitude of the conducted count.

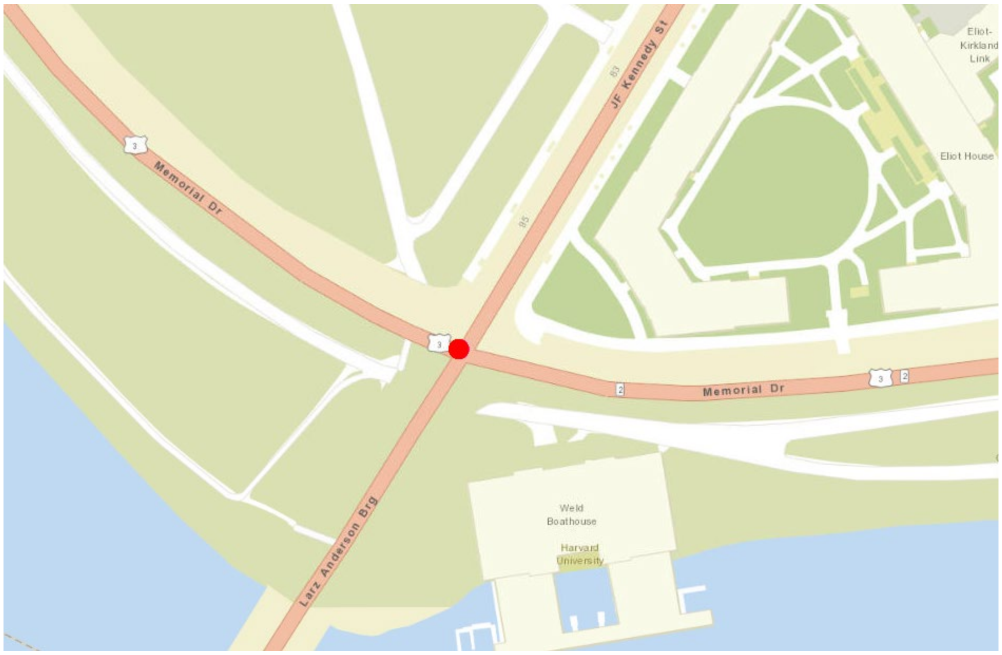
For this study, the research team extracted the 2016 (September 13, 2016) and 2019 (September 17, 2019) data for further analysis. In addition, the team obtained the permanent bicycle count data from its website for similar dates and times as in the temporary bicycle count data.[22]

The permanent bicycle counter device is assumed to slightly undercount the number of bicyclists because some of the bicyclists probably do not use the designated bicycle path to cross the road. To address this issue, the city conducted tube and manual counts to determine the missing number of bicyclists. The results indicated that an adjustment factor of 1.167 could be used for considering the missing bicyclists from the permanent bicycle counter.[22] Therefore, all the retrieved values from the permanent count station were multiplied by 1.167 to reflect the actual number of bicyclists.

The research team also acquired land use data for the study area.[1]

DATA MANIPULATION AND PREPARATION

The research team then developed the estimated exposure thresholds for each site in the study area. To illustrate this development, this section explains the data preparation process for one example (the intersection of Anderson Bridge and John F. Kennedy (JFK) Street at Memorial Drive) (figure 2). The average daily traffic count data used for this demonstration was acquired from the Cambridge open data website.[23]



Original map © 2019 Google® Earth™ (see Acknowledgments).

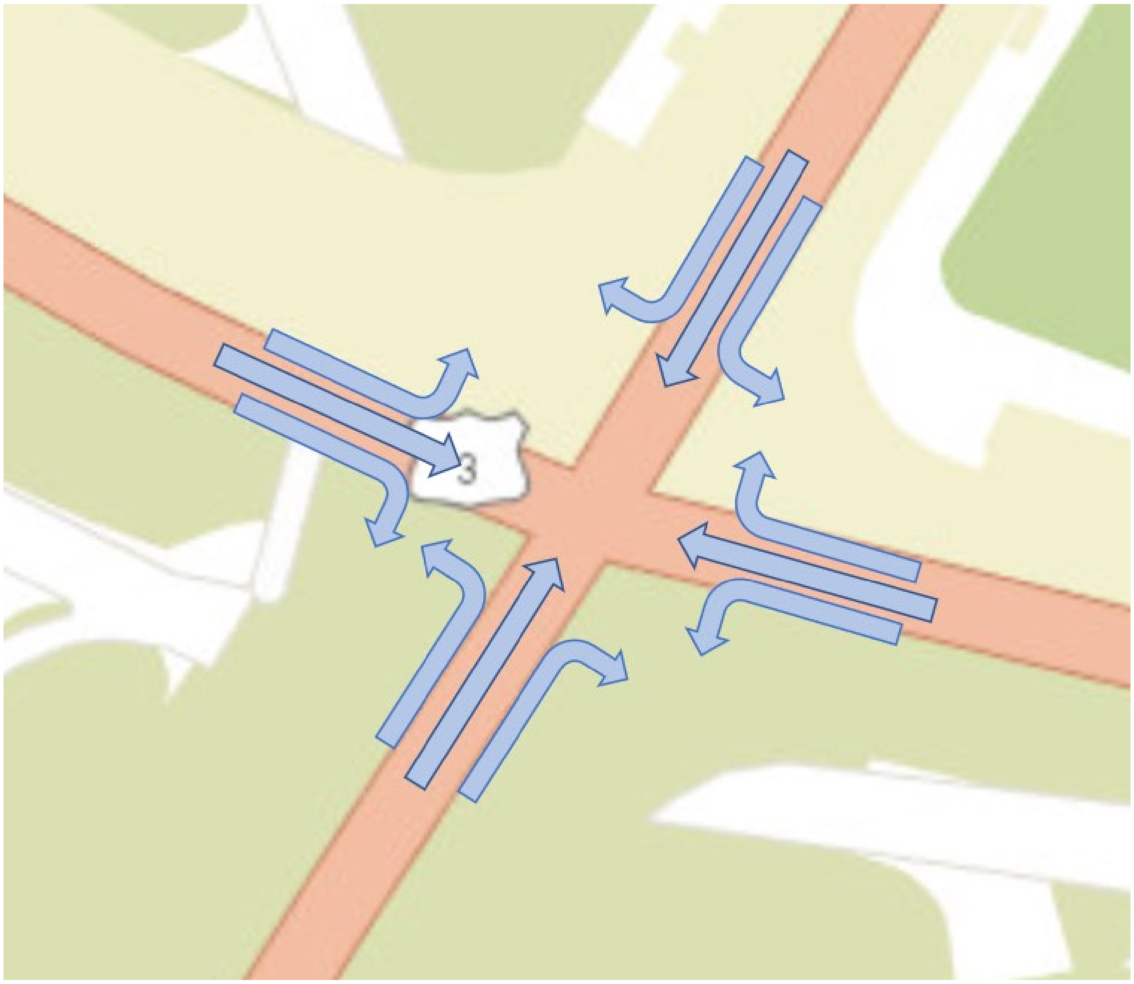
Figure 2. Map. Anderson Bridge and JFK Street at Memorial Drive in Cambridge.(24)

Table 6 provides a part of the original dataset from the intersection of Anderson Bridge and JFK Street and Memorial Drive collected by Cambridge. Specifically, the table shows data were collected on bicyclists who arrived to or departed from the intersection and made either right, left, or through movements between 7:15 a.m. and 7:30 a.m. on September 17, 2019. In addition, the data include whether bicyclists rode with or against the traffic and on either street or sidewalk.

Table 6. Data table for Anderson Bridge, JFK Street, and Memorial Drive in Cambridge.

Count Location	Year	Date	Time Period	Time	Street	Traffic Direction	Cyclist Location	Cyclist Direction	Movement	Count	Temp (°F)	Weather
Anderson Bridge and JFK St. and Memorial Dr.	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Street	With traffic	Left	0	52	Clear
Anderson Bridge and JFK St. and Memorial Dr	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Street	Against traffic	Left	0	52	Clear
Anderson Bridge and JFK St. and Memorial Dr.	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Sidewalk	With traffic	Left	0	52	Clear
Anderson Bridge and JFK St. and Memorial Dr.	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Sidewalk	Against traffic	Left	0	52	Clear
Anderson Bridge and JFK St. and Memorial Dr.	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Street	With traffic	Right	2	52	Clear
Anderson Bridge and JFK St. and Memorial Dr.	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Street	Against traffic	Right	0	52	Clear
Anderson Bridge and JFK St. and Memorial Dr.	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Sidewalk	With traffic	Right	0	52	Clear
Anderson Bridge and JFK St. and Memorial Dr.	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Sidewalk	Against traffic	Right	0	52	Clear
Anderson Bridge and JFK St. and Memorial Dr.	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Street	With traffic	Through	10	52	Clear
Anderson Bridge and JFK St. and Memorial Dr.	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Street	Against traffic	Through	0	52	Clear
Anderson Bridge and JFK St. and Memorial Dr.	2019	9/17/2019	AM	7:30	JFK St.	Northbound	Sidewalk	With traffic	Through	0	52	Clear

Figure 3 depicts all the movements of the bicyclists at the intersection, regardless of whether they are riding with or against the traffic. A bicycle path is located parallel to Memorial Drive, but the movements are not indicated in the figure because bicycle paths are not within the scope of this research.

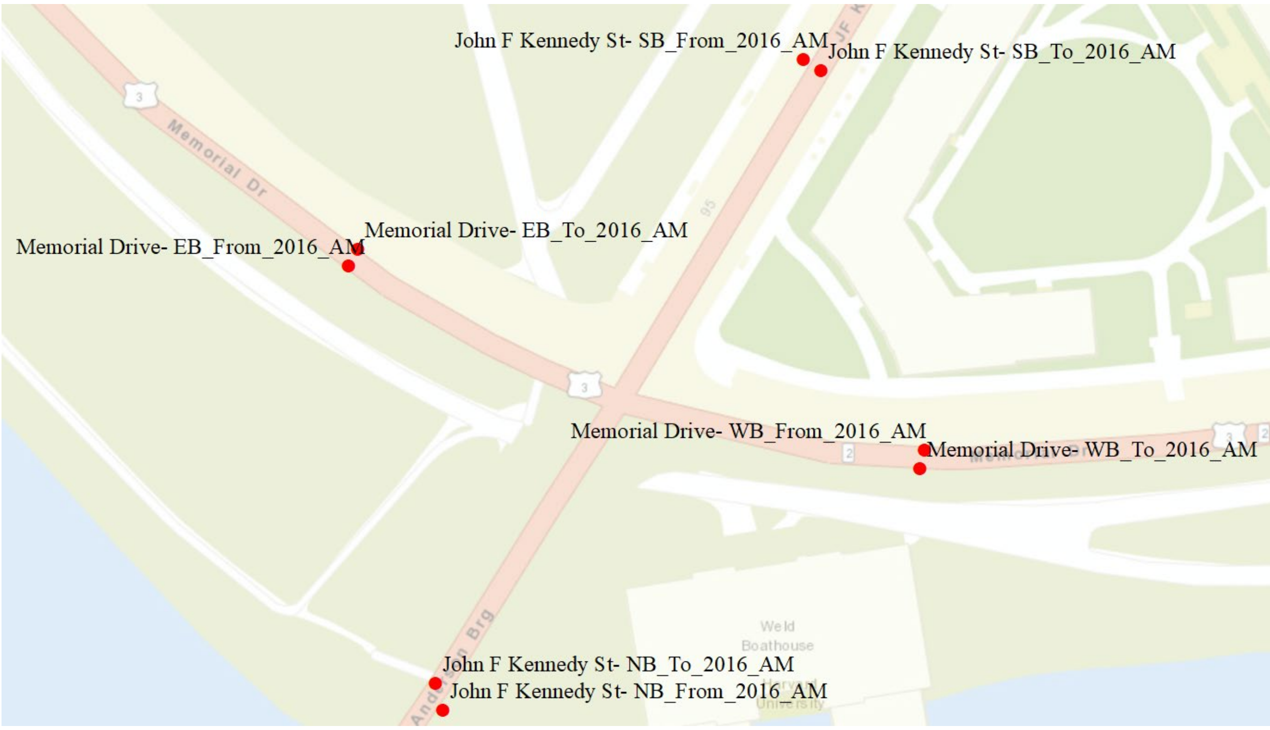


Original map © 2019 Google® Earth™ (see Acknowledgments).

Figure 3. Map. Bicycle movements at the intersection of Anderson Bridge and JFK Street and Memorial Drive in Cambridge.(23,24)

To better analyze the data, the research team labeled the data to indicate from which street the bicyclists are coming and to which street they are going. The team manually determined and labeled the origin and destination of the bicyclists by using the variables *Street*, *Traffic Direction*, and *Movement Type* for each leg of all the study intersections. The new variables were called *From* and *To*, respectively. For instance, the southbound road was labeled as "John F. Kennedy St.–SB" and the eastbound as "Memorial Dr.–EB." Hence, the origin for the bicyclists that were going southbound and turning right was "John F. Kennedy St.–SB," and the destination was "Memorial Dr.–EB." Moreover, the direction of bicyclists was included in the variables because direction is an important factor for aggregating the count data in the next steps. Taking this example into consideration, the origin of the bicyclists would be "John F. Kennedy St.–SB–*From*," and the destination would be "Memorial Dr.–EB–*To*."

Two additional variables included the *Year* and *Time Period*. These variables were also considered in the development of the final *From* and *To* variables. Table 7 represents the data table, including the new variables. Figure 4 graphically depicts a few data points and their associated names after manipulating and labeling the original dataset.



Original map © 2019 Google® Maps™ (see Acknowledgments).
NB = northbound; WB = westbound.

Figure 4. Map. Cambridge data points with labels.[23,24]

Table 7. Updated data table for Anderson Bridge, JFK Street, and Memorial Drive in Cambridge, including origin and destination.

Count Location	Street	From	To	Year	Date	Time Period	Traffic Direction	Movement Type
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–SB	John F. Kennedy St.–SB_From_2016_AM	John F. Kennedy St.–NB_To_2016_AM	2016	9/13/2016	AM	Southbound	Through
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–SB	John F. Kennedy St.–SB_From_2019_AM	John F. Kennedy St.–NB_To_2019_AM	2019	9/17/2019	AM	Southbound	Through
Anderson Bridge and JFK St. and Memorial Dr.	John F Kennedy St.–SB	John F. Kennedy St.–SB_From_2016_PM	John F. Kennedy St.–NB_To_2016_PM	2016	9/13/2016	PM	Southbound	Through
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–SB	John F. Kennedy St–SB_From_2019_PM	John F. Kennedy St.–NB_To_2019_PM	2019	9/17/2019	PM	Southbound	Through
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–NB	John F. Kennedy St–NB_From_2016_AM	John F. Kennedy St.–SB_To_2016_AM	2016	9/13/2016	AM	Northbound	Through
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–NB	John F. Kennedy St–NB_From_2019_AM	John F. Kennedy St.–SB_To_2019_AM	2019	9/17/2019	AM	Northbound	Through
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–NB	John F. Kennedy St–NB_From_2016_PM	John F. Kennedy St.–SB_To_2016_PM	2016	9/13/2016	PM	Northbound	Through
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–NB	John F. Kennedy St–NB_From_2019_PM	John F. Kennedy St.–SB_To_2019_PM	2019	9/17/2019	PM	Northbound	Through
Anderson Bridge and JFK St. and Memorial Dr.	John F, Kennedy St.–NB	John F. Kennedy St–NB_From_2016_AM	Memorial Drive–EB_To_2016_AM	2016	9/13/2016	AM	Northbound	Through
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–NB	John F. Kennedy St–NB_From_2019_AM	Memorial Drive–EB_To_2019_AM	2019	9/17/2019	AM	Northbound	Left

Count Location	Street	From	To	Year	Date	Time Period	Traffic Direction	Movement Type
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–NB	John F. Kennedy St.–NB_From_2016_PM	Memorial Drive–EB_To_2016_PM	2016	9/13/2016	PM	Northbound	Left
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–NB	John F. Kennedy St.–NB_From_2019_PM	Memorial Drive–EB_To_2019_PM	2019	9/17/2019	PM	Northbound	Left
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–SB	John F. Kennedy St.–SB_From_2016_AM	Memorial Drive–EB_To_2016_AM	2016	9/13/2016	AM	Southbound	Right
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–SB	John F. Kennedy St.–SB_From_2019_AM	Memorial Drive–EB_To_2019_AM	2019	9/17/2019	AM	Southbound	Right
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–SB	John F. Kennedy St.–SB_From_2016_PM	Memorial Drive–EB_To_2016_PM	2016	9/13/2016	PM	Southbound	Right
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–SB	John F. Kennedy St.–SB_From_2019_PM	Memorial Drive–EB_To_2019_PM	2019	9/17/2019	PM	Southbound	Right
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–NB	John F. Kennedy St.–NB_From_2016_AM	Paul Dudley White Path–WB_To_2016_AM	2016	9/13/2016	AM	Northbound	Right
Anderson Bridge and JFK St. and Memorial Dr.	John F. Kennedy St.–NB	John F. Kennedy St.–NB_From_2019_AM	Paul Dudley White Path–WB_To_2019_AM	2019	9/17/2019	AM	Northbound	Right

STATISTICAL MODELING

The main purpose of preparing the dataset was to develop bicycle surrogate exposure models for Cambridge, MA. Therefore, in addition to the bicycle count data, the research team collected and developed new variables. These variables, as defined by the team, included the following factors:

- Average daily traffic (ADT): Researchers obtained the ADT data from the City of Cambridge Open Data Portal.[23]
- Land use: Researchers downloaded the land-use data from the geographic information system of the City of Cambridge.[1]
- Residential binary: Researchers defined this new variable as an extension of the variable land use. Residential binary indicates whether the dominant land use near a bicycle counter was residential.
- Population density: Researchers downloaded the population and area (m^2) information at the census tract level from the American Community Survey data.[25] This variable includes the population density (people/mi^2) for each census tract.
- Bicycle facility type: Researchers collected this information from aerial views to represent the type of bicycle facility, such as SBL, painted bicycle lane (with and without a buffer), and no bicycle lane.
- Length of bicycle lanes within 1 mi of the bicycle counters: Researchers determined the bicycle facilities within Cambridge using a Web mapping platform.[24] The data were imported to a geospatial mapping software system for additional analysis. Team members drew buffers with 1-mi radii around each bicycle counter. Eventually, the team measured the length of bicycle miles within each buffer. The measurements considered each direction of travel separately.
- Bicycle lane continuity: Researchers developed this variable from an aerial view to indicate whether a counter is located on a roadway with a continuous bicycle facility (i.e., the bicycle lane does not stop and start as a result of adjacent development).
- One-way roadway: Researchers used aerial views on a Web mapping platform to determine whether the roadway of interest operated as a one-way facility.
- Presence of bicycle lane: Researchers collected this variable from aerial views. The variable is a binary value and indicates whether a bicycle lane exists, regardless of the facility type.

Because the data are short-term counts and the AADB data are not available, two different approaches were considered for developing bicycle surrogate models:

- Conducting two separate models for AM and PM peaks.
- Developing peak-hour data models.

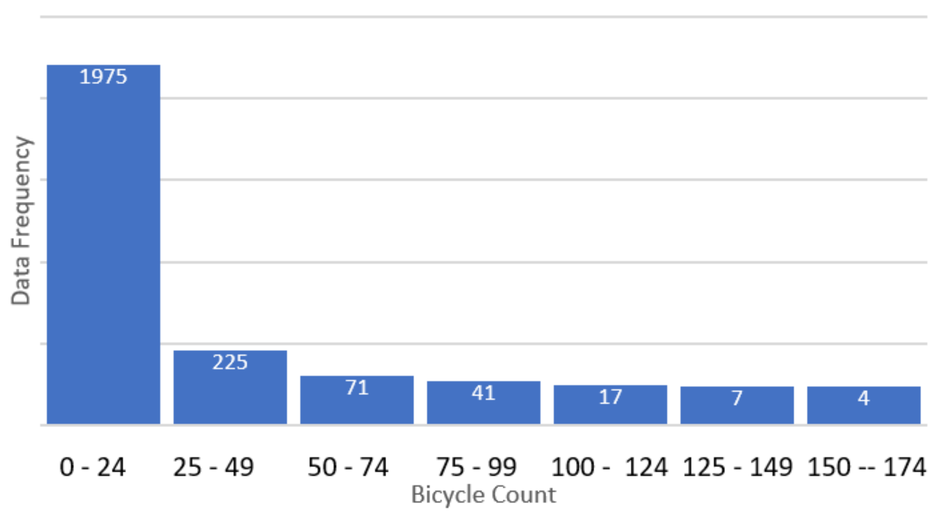
In other words, the team developed two different sets of models for AM and PM data. Moreover, the research team calculated hourly data using the given 15-min data throughout to estimate the peak-hour volume. The peak-hour data for each leg of each intersection were used to developed peak-hour surrogate models. The following sections cover each separate analysis approach.

AM and PM Models (15 Min)

The original dataset provided 15-min bicycle count data for the AM and PM periods. In this section, the team directly used the given data to develop AM and PM bicycle surrogate models.

AM Models (15 Min)

Figure 5 shows the distribution of the 2,340 available bicycle count data points observed for the AM period, and table 8 provides the descriptive statistics of the study variables.



Source: FHWA.

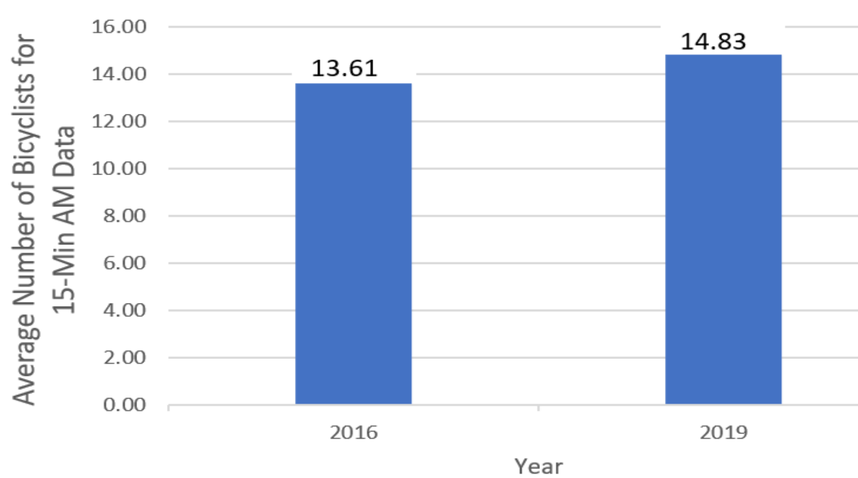
Figure 5. Chart. Distribution of AM 15-min bicycle count data for Cambridge bicycle volume.

Table 8. Descriptive statistics of the study variable for the 15-min AM data for Cambridge.

Variable	Mean	Standard Deviation	Minimum	Maximum
Count	14.22	20.42	0	160
ADT (vpd)	11,073.09	7,136.59	1,032	24,264
Length (mi) of bicycle lanes within 1 mi	11.98	3.12	4.96	15.67
Presence of one-way roadway (1 = yes)	0.25	0.43	0	1
Presence of continuous bicycle lane (1 = yes)	0.51	0.50	0	1
Presence of separated bicycle lane (1 = yes)	0.41	0.52	0	2
Population density (pop/mi^2)	20,428.16	10,367.45	5,692	49,022
Presence of bicycle lane (1 = yes)	0.49	0.50	0	1
Presence of residential development (1 = yes)	0.15	0.36	0	1

pop = population; vpd = vehicles per day.

Figure 6 represents the average bicycle count data over all the sites for each year separately. No noticeable increase/decrease in the average count occurred from 2016 to 2019. Cambridge provides bicycle count data every other year, but due to severe winter weather followed by unusually high heat trends in 2018, the city collected bicycle count data in 2019 as well. Table 9 and table 10 summarize the average number of bicycles for each bicycle facility and land use, respectively.



Source: FHWA.

Figure 6. Chart. Average AM 15-min bicycle count data for the Cambridge study years (2016–2019).

Table 9. Frequency of various bicycle facility types for the 15-min AM data for Cambridge.

Bicycle Facility Type	Frequency (No./15 min.)
No bicycle lane	1,200
Painted bicycle lanes/no buffer	884
Painted bicycle lanes with buffer adjacent to active travel lane	80
Separated bicycle lane with buffer and vertical element	176
Total	2,340

Table 10. Frequency of various land uses for the 15-min AM data for Cambridge.

Land Use	Frequency (No./15 min.)
Commercial	560
Mixed use	160
None	64
Open space	128
Other	1,072
Residential	356
Total	2,340

Next, the research team conducted a correlation test to determine any correlations between the independent variables. Table 11 provides the results of the correlation test.

Table 11. Correlation test for the 15-min AM data for Cambridge.

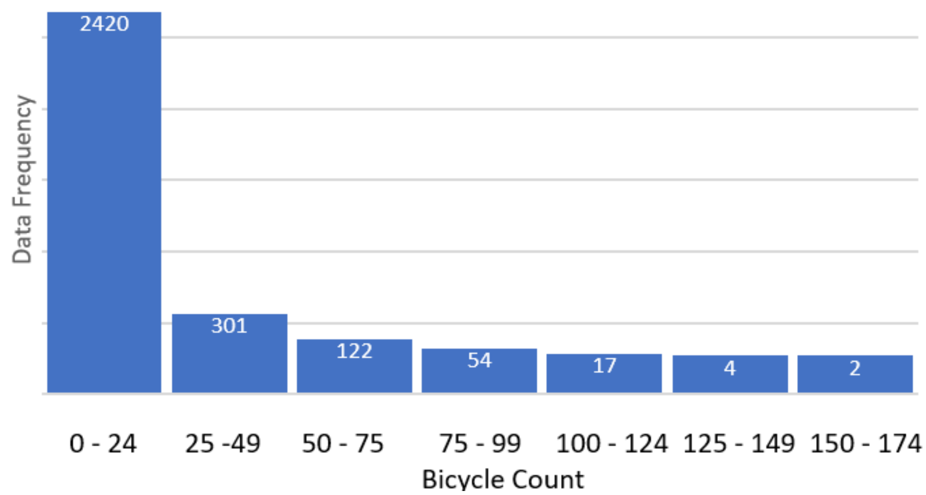
Variable	Population Density/ 1,000 Persons	Continuous Bicycle Lane	One-Way Roadway	Presence of Bicycle Lane	Separated Bicycle Lane	Length (mi) of Bicycle Lanes Within 1 Mi	Residential Binary	Log (ADT)	ADT/ 1,000 Per Day
Population density/1,000 persons	***1***	—	—	—	—	—	—	—	—
Continuous bicycle lane (1 = yes)	−0.06	***1***	—	—	—	—	—	—	—
One-way roadway (1 = yes)	0.04	−0.06	***1***	—	—	—	—	—	—
Presence of bicycle lane (1 = yes)	−0.11	***0.83***	−0.19	***1***	—	—	—	—	—
Separated bicycle lane (1 = yes)	−0.10	***0.74***	−0.26	***0.77***	***1***	—	—	—	—
Length (mi) of bicycle lanes within 1 mi	−0.07	0.02	0.10	0.06	0.02	***1***	—	—	—
Residential (1 = yes)	−0.12	−0.11	0.13	−0.10	−0.04	0.20	***1***	—	—
Log(ADT)	0.06	0.26	−0.42	0.25	0.19	−0.05	−0.17	***1***	—
ADT/1,000	0.13	0.20	−0.43	0.20	0.13	−0.22	−0.24	***0.92***	***1***

Log = logarithm.
Note: Values shown as bold indicate variable correlation of 0.7 or higher.

The research team considered using nested mixed-effect regression models because each single study intersection has multiple legs, and each leg has multiple data points to represent 15-min intervals. In the models, two variables of intersection (represented as *CountLoc*) and study location (defined as *Group*) were considered as random-effect variables where CountLoc represents the physical location of each count. The following sections provide the results of nested mixed-effect Poisson and nested mixed-effect negative binomial models, respectively.

PM Models (15-Min)

The PM period included 2,920 data points, and figure 7 shows the distribution of PM bicycle count data. Table 12 provides the descriptive statistics of the study variables.



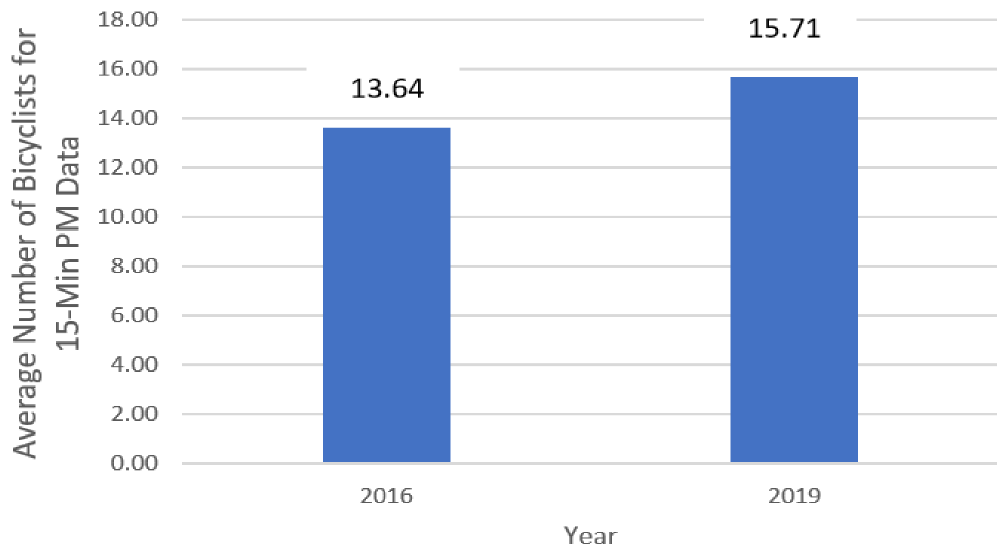
Source: FHWA.

Figure 7. Chart. Distribution for Cambridge PM 15-min bicycle count data.

Table 12. Descriptive statistics of the study variable for the 15-min PM data for Cambridge.

Variable	Mean	Standard Deviation	Minimum	Maximum
Count	14.67	19.94	0	170
ADT (vpd)	11,085.18	7,136.41	1,032	24,264
Length (mi) of bicycle lanes within 1 mi	11.97	3.12	4.96	15.67
One-way roadway (1 = yes)	0.25	0.43	0	1
Continuous bicycle lane (1 = yes)	0.51	0.50	0	1
Separated bicycle lane (1 = yes)	0.41	0.52	0	2
Population density (pop/mi^2)	20,420.47	10,374.21	5,692	49,022
Presence of bicycle lane (1= yes)	0.49	0.50	0	1
Residential (1 = yes)	0.15	0.36	0	1

Figure 8 shows the average PM bicycle counts for the study years, and table 13 and table 14 provide the frequency of each bicycle facility and land use types for the PM data, respectively.



Source: FHWA.

Figure 8. Chart. Average PM 15-min bicycle count data for the Cambridge study years.

Table 13. Frequency of various bicycle facility types for the Cambridge 15-min PM data.

Bicycle Facility Type	Frequency (No.)
No bicycle lane	1,500
Painted bicycle lanes/no buffer	1,100
Painted bicycle lanes with buffer adjacent to active travel lane	100
Separated bicycle lane with buffer and vertical element	220
Total	2,920

Table 14. Frequency of various land uses for the 15-min PM data for Cambridge.

Land Use	Frequency (No.)
Commercial	700
Mixed use	200
None	80
Open space	160
Other	1,340
Residential	440
Total	2,920

In a manner similar to the AM data modeling effort, the research team conducted a correlation test to determine any possible correlation between the study variables before developing the surrogate models. Table 15 represents the correlation test results.

Table 15. Correlation test for the 15-min PM data.

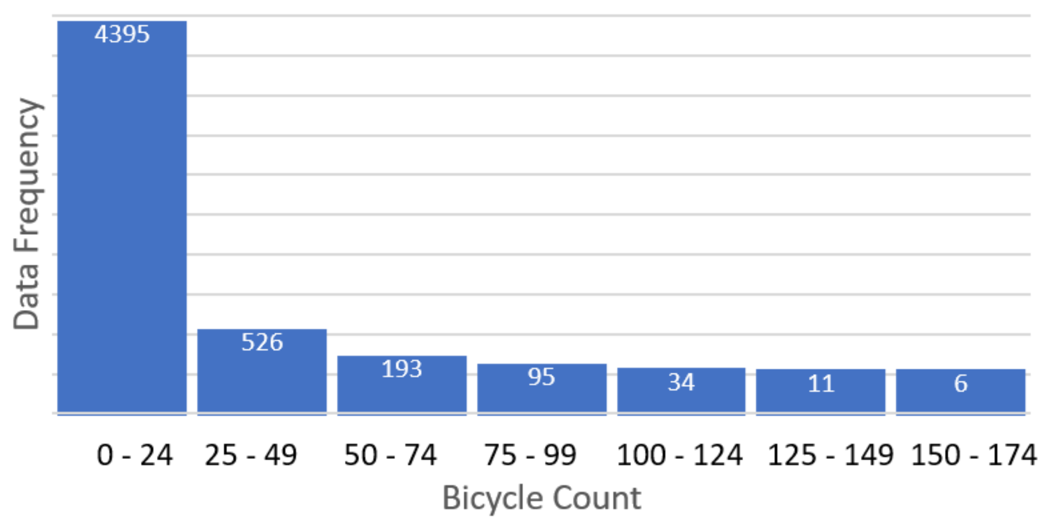
Variable	ADT	Population Density/1,000	Continuous Bicycle Lane	One-Way Roadway	Presence of Bicycle Lane	Separated Bicycle Lane	Length (mi) of Bicycle Lanes Within 1 Mi	Residential Binary	Log (ADT)
ADT (vpd)	***1***	—	—	—	—	—	—	—	—
Population density/ 1,000 persons	0.15	***1***	—	—	—	—	—	—	—
Continuous bicycle lane (1 = yes)	0.25	−0.07	***1***	—	—	—	—	—	—
One-way roadway (1 = yes)	−0.42	0.02	−0.07	***1***	—	—	—	—	—
Presence of bicycle lane (1 = yes)	0.25	−0.12	***0.82***	−0.21	***1***	—	—	—	—
Separated bicycle lane (1 = yes)	0.17	−0.11	***0.73***	−0.27	***0.76***	***1***	—	—	—
Length (mi) of bicycle lanes within 1 mi	−0.19	−0.09	0.00	0.08	0.05	0.01	***1***	—	—
Residential (1 = yes)	−0.24	−0.13	−0.12	0.11	−0.10	−0.04	0.19	***1***	—
Log(ADT)	*0.92*	0.07	0.30	−0.42	0.29	0.22	−0.02	−0.15	***1***

Note: Values shown as bold indicate variable correlation of 0.7 or higher.

Next, the team developed nested mixed-effect negative binomial models and nested mixed-effect Poisson models, which were developed by using the variables *CountLoc* and *Group* as the random-effect variables where CountLoc refers to the physical location of the bicycles.

Aggregated 15-Min AM and PM Models

The dataset included 5,260 data points when aggregating AM and PM 15-min data for the study sites. Figure 9 represents the distribution of the bicycle count data, and table 16 provides descriptive statistics of the study variables.



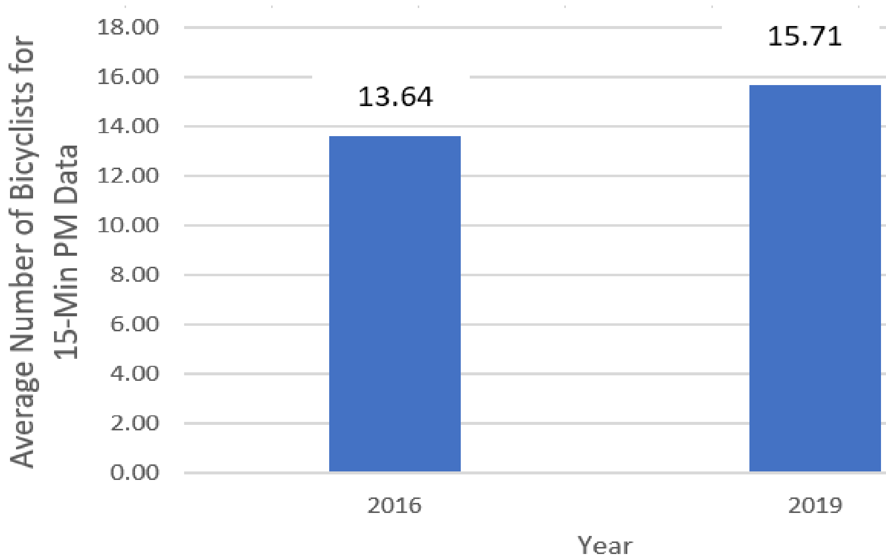
Source: FHWA.

Figure 9. Chart. Distribution of the aggregated 15-min AM and PM bicycle count data for Cambridge.

Table 16. Descriptive statistics of the study variable for the aggregated 15-min AM and PM bicycle count data for Cambridge.

Variable	Mean	Standard Deviation	Minimum	Maximum
Bicycle count	14.47	20.15	0	170
ADT (vpd)	11,079.80	7,135.81	1,032	24,264
Length (mi) of bicycle lanes within 1 mi	11.97	3.12	4.96	15.67
One-way roadway (1 yes)	0.25	0.43	0	1
Continuous bicycle lane (1 = yes)	0.51	0.50	0	1
Separated bicycle lane (1 = yes)	0.41	0.52	0	2
Population density (pop/mi^2)	20,423.89	10,370.22	5,692	49,022
Presence of bicycle lane (1 = yes)	0.49	0.50	0	1

Additionally, figure 10, table 17, and table 18 provide information about the average bicycle count data for each year as well as the frequency of various bicycle facilities and land uses.



Source: FHWA.

Figure 10. Chart. Distribution for Cambridge aggregated 15-min AM and PM bicycle count data for the study years.

Table 17. Frequency of various bicycle facility types for the aggregated 15-min AM and PM bicycle count data for Cambridge.

Bicycle Facility Type	Frequency (No.)
No bicycle lane	2,700
Painted bicycle lanes/no buffer	1,984
Painted bicycle lanes with buffer adjacent to active travel lane	180
Separated bicycle lane with buffer and vertical element	396
Total	5,260

Table 18. Frequency of various land uses for the aggregated 15-min AM and PM bicycle count data for Cambridge.

Land Use	Frequency (No.)
Commercial	1,260
Mixed use	360
None	144
Open space	288
Other	2,412
Residential	796
Total	5,260

The research team conducted another Pearson's correlation test before the development of regression models (see table 19).

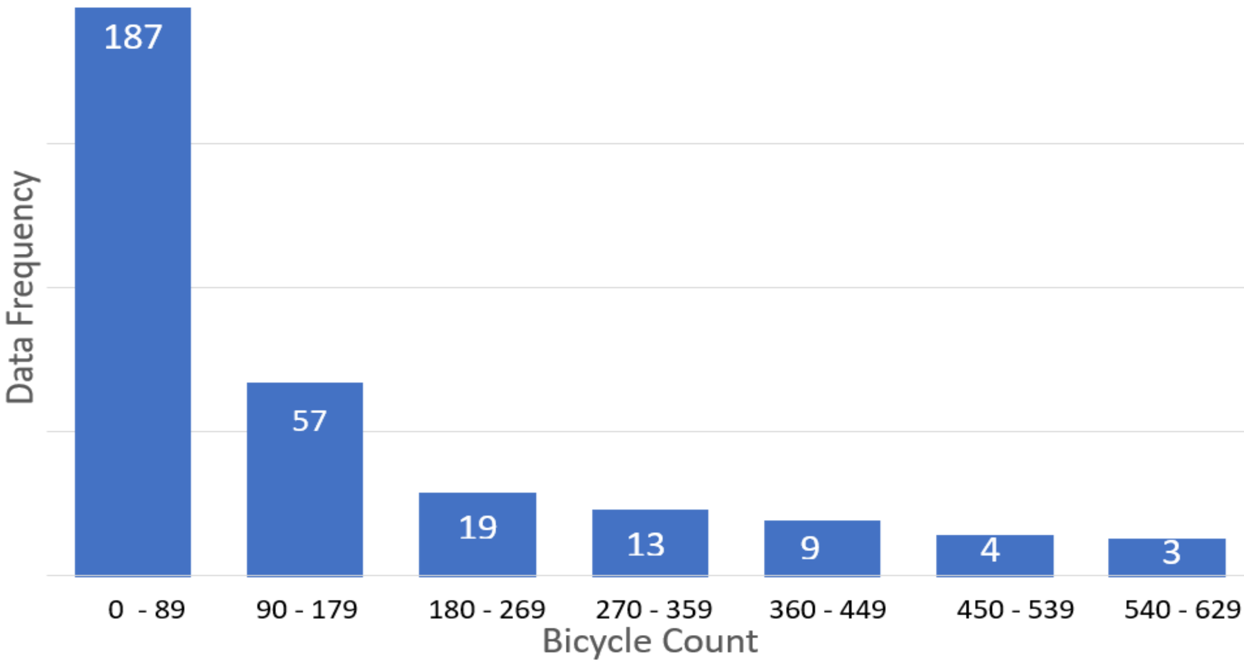
Table 19. Correlation test for the aggregated 15-min AM and PM bicycle count data for Cambridge.

Variable	Population Density/ 1,000	Continuous Bicycle Lane	One-Way Roadway	Presence of Bicycle Lane	Separated Bicycle Lane	Length (mi) of Bicycle Lanes within 1 Mi	Residential Binary	Log (ADT)	ADT/ 1,000
Population density/1,000	***1***	—	—	—	—	—	—	—	—
Continuous bicycle lane	−0.07	***1***	—	—	—	—	—	—	—
One-way roadway	0.03	−0.07	***1***	—	—	—	—	—	—
Presence of bicycle lane	−0.12	***0.82***	−0.21	***1***	—	—	—	—	—
Separated bicycle lane	−0.11	***0.73***	−0.27	***0.76***	***1***	—	—	—	—
Length (mi) of bicycle lanes within 1 mi	−0.09	0.00	0.09	0.05	0.01	***1***	—	—	—
Residential binary	−0.13	−0.12	0.12	−0.10	−0.04	0.19	***1***	—	—
Log(ADT)	0.07	0.30	−0.42	0.29	0.22	−0.02	−0.16	*1*	—
ADT/1,000	0.15	0.25	−0.42	0.25	0.17	−0.19	−0.24	***0.92***	***1***

Note: Values shown as bold indicate variable correlation of 0.7 or higher.

Peak-Hour Models

The peak-hour data contained 292 observations. Figure 11 depicts the distribution of the peak-hour bicycle count data for the study sites, and table 20 provides descriptive statistics of the peak-hour data.



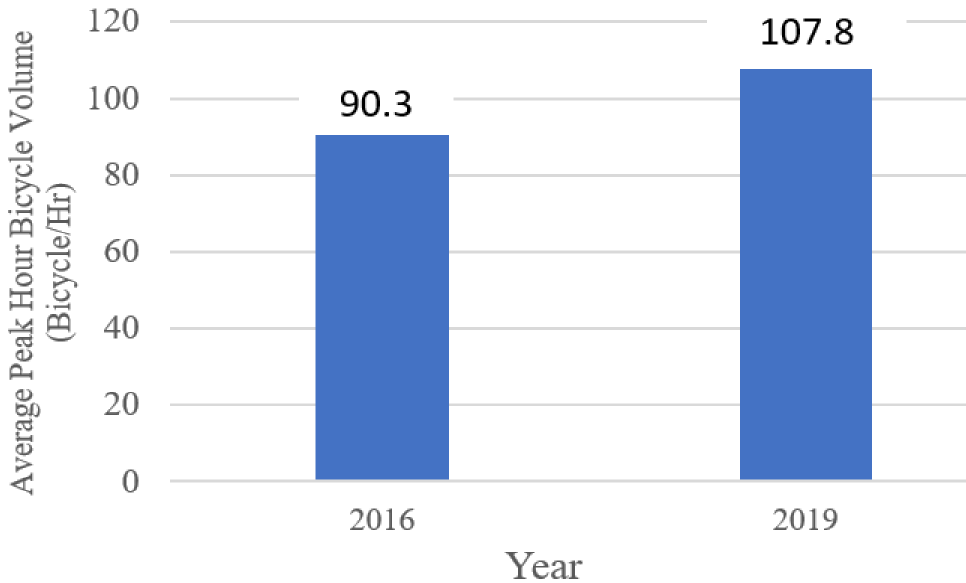
Source: FHWA.

Figure 11. Chart. Distribution for Cambridge peak-hour bicycle count data by hourly volume.

Table 20. Descriptive statistics of the study variable for the peak hour.

Variable	Mean	Standard Deviation	Minimum	Maximum
Peak-hour bicycle volume	99.05	113.63	0	582
ADT (vpd)	11,085.18	7,147.44	1,032	24,264
Length (mi) of bicycle lanes within 1 mi	11.97	3.13	4.96	15.67
One-way roadway (1 = yes)	0.25	0.43	0	1
Continuous bicycle lane (1 = yes)	0.51	0.50	0	1
Separated bicycle lane (1 = yes)	0.41	0.52	0	2
Population density (pop/mi^2) (1 = yes)	0.49	0.50	0	1
Presence of bicycle lane (1 = yes)	0.15	0.36	0	1
Residential (1 = yes)	0.15	0.36	0	1

Figure 12 shows the average peak-hour bicycle counts over all the study sites for each year separately. As depicted, in 2019, the number of bicyclists increased over that observed for 2016. Table 21 and table 22 show the distribution of each bicycle facility and land use type, respectively.



Source: FHWA.

Figure 12. Chart. Distribution of Cambridge peak-hour bicycle count data for the study years (2016–2019).

Table 21. Frequency of various bicycle facility types for the peak hour.

Bicycle Facility Type	Frequency (No.)
No bicycle lane	150
Painted bicycle lanes/no buffer	110
Painted bicycle lanes with buffer adjacent to active travel lane	10
Separated bicycle lane with buffer and vertical element	22
Total	292

Table 22. Frequency of various land uses for the peak-hour data.

Land Use	Frequency (No.)
Commercial	70
Mixed use	20
None	8
Open space	16
Other	134
Residential	44
Total	292

The research team considered the results of the correlations tests, represented in table 23, to guide variable selections when developing the bicycle surrogate models.

Table 23. Correlation test for Cambridge peak-hour data.

Variable	Population Density/ 1,000	Continuous Bicycle Lane	One-Way Roadway	Presence of Bicycle Lane	Separated Bicycle Lane	Length (mi) of Bicycle Lanes within 1 Mi	Residential Binary	Log (ADT)	ADT/ 1,000
Population density/1,000	***1***	—	—	—	—	—	—	—	—
Continuous bicycle lane (1 =1 yes)	−0.07	***1***	—	—	—	—	—	—	—
One-way roadway (1 = yes)	0.02	−0.07	***1***	—	—	—	—	—	—
Presence of bicycle lane (1 = yes)	−0.12	***0.82***	−0.21	***1***	—	—	—	—	—
Separated bicycle lane (1 = yes)	−0.11	***0.73***	−0.27	***0.76***	***1***	—	—	—	—
Length (mi) of bicycle lanes within 1 mi	−0.09	0.00	0.08	0.05	0.01	***1***	—	—	—
Residential (1 = yes)	−0.13	−0.12	0.11	−0.10	−0.04	0.19	***1***	—	—
Log(ADT)	0.07	0.30	−0.42	0.29	0.22	−0.02	−0.15	***1***	—
ADT/1,000	0.15	0.25	−0.42	0.25	0.17	−0.19	−0.24	***0.92***	***1***

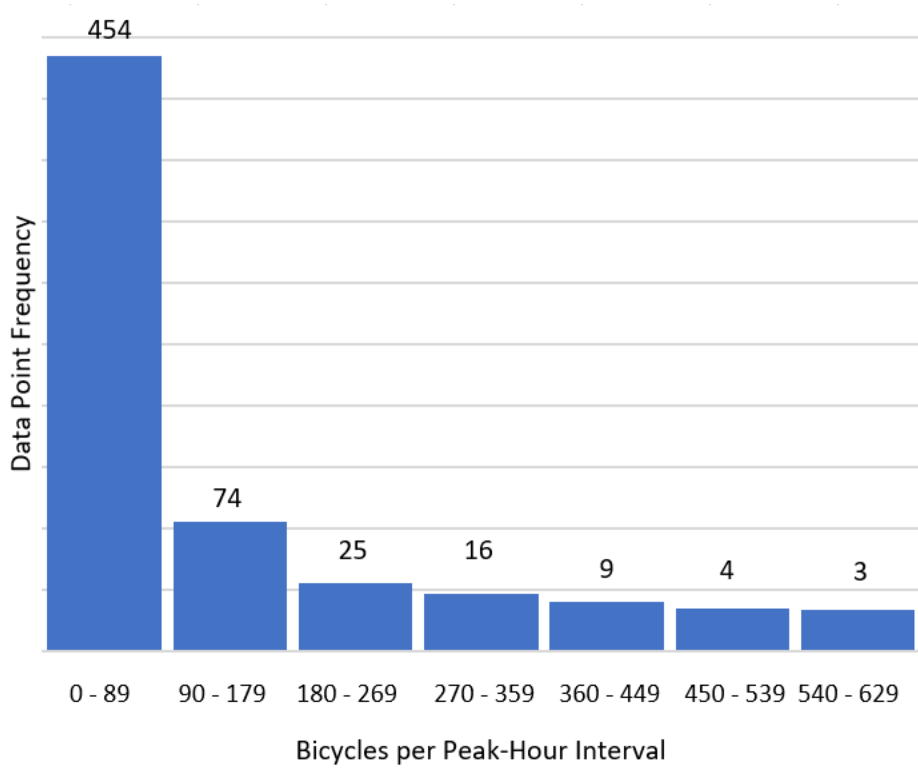
Note: Values shown as bold indicate variable correlation of 0.7 or higher.

Nested Mixed-Effect Negative Binomial

Although the research team made several attempts to statistically develop a nested mixed-effect negative binomial model, they were unable to identify any models that converged.

Aggregated AM and PM Peak-Hour Models

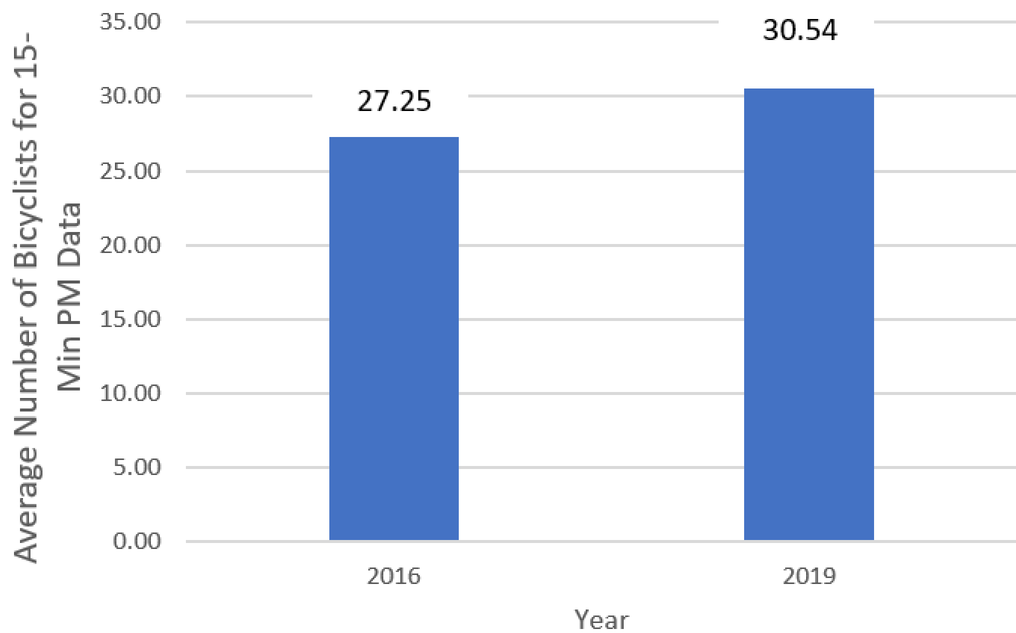
In this section, the research team considered both the AM and PM peak-hour data points for each location in the analysis. The dataset included 585 observations. Figure 13 depicts the distribution of the peak-hour bicycle count data for the study sites. The trends observed for the AM and PM as well as average AADB, as shown in the AM and PM summaries, are consistent with the aggregated summary.



Source: FHWA.

Figure 13. Chart. Distribution of Cambridge aggregated AM and PM peak-hour count data.

Figure 14 indicates the average peak-hour bicycle count over all the study sites for each year separately. As depicted, the number of bicyclists was higher in 2019 than in 2016. Table 24 provides descriptive statistics of the peak-hour data. Table 25 and table 26 show the distribution of each bicycle facility and land-use type, respectively.



Source: FHWA.

Figure 14. Chart. Distribution of Cambridge aggregated peak-hour bicycle count data for the PM periods.

Table 24. Descriptive statistics of the study variable for the aggregated AM and PM peak hour.

Variable	Mean	Standard Deviation	Minimum	Maximum
Peak-hour bicycle volume (count)	70.36	92.71	0	582
ADT (vpd)	11,073.09	7,141.17	1,032	24,264
Length (mi) of bicycle lanes within 1 mi	11.98	3.13	4.96	15.67
One-way roadway (1 = yes)	0.25	0.43	0	1
Continuous bicycle lane (1 = yes)	0.51	0.50	0	1
Separated bicycle lane (1 = yes)	0.41	0.52	0	2
Population density (pop/mi^2)	20,428.16	10,374.11	5,692	49,022
Presence of bicycle lane (1 = yes)	0.49	0.50	0	1

Table 25. Frequency of various bicycle facility types for the aggregated AM and PM peak-hour data.

Bicycle Facility Type	Frequency (No.)
No bicycle lane	300
Painted bicycle lanes/no buffer	221
Painted bicycle lanes with buffer adjacent to active travel lane	20
Separated bicycle lane with buffer and vertical element	44
Total	585

Table 26. Frequency of various land uses for the aggregated AM and PM peak-hour data.

Land Use	Frequency (No.)
Commercial	140
Mixed use	40
None	16
Open space	32
Other	268
Residential	89
Total	585

The research team considered the results of the correlations tests, represented in table 27, for conducting the bicycle surrogate models.

Table 27. Correlation test for the aggregated AM and PM peak-hour data.

Variable	Population Density/ 1,000	Continuous Bicycle Lane	One-Way Roadway	Presence of Bicycle Lane	Separated Bicycle Lane	Length (mi) of Bicycle Lanes within 1 Mi	Residential Binary	Log (ADT)	ADT/ 1,000
Population density/1,000	***1***	—	—	—	—	—	—	—	—
Continuous bicycle lane (1 = yes)	−0.07	***1***	—	—	—	—	—	—	—
One-way roadway (1 = yes)	0.03	−0.07	***1***	—	—	—	—	—	—
Presence of bicycle lane (1 = yes)	−0.13	***0.86***	−0.24	***1***	—	—	—	—	—
Separated bicycle lane (1 = yes)	−0.11	***0.73***	−0.27	***0.82***	***1***	—	—	—	—
Length (mi) of bicycle lanes within 1 mi	−0.09	0.00	0.09	0.06	0.01	***1***	—	—	—
Residential (1 = yes)	−0.12	−0.12	0.12	−0.10	−0.04	0.19	***1***	—	—
Log(ADT)	0.07	0.30	−0.42	0.30	0.22	−0.02	−0.16	***1***	—
ADT/1,000	0.15	0.25	−0.43	0.26	0.18	−0.20	−0.24	***0.92***	***1***

Note: Values shown as bold indicate variable correlation of 0.7 or higher.

Nested Mixed-Effect Negative Binomial

No nested mixed-effect negative binomial models converged for this dataset. Models included *Year* as a potential variable, but the results indicated this variable was insignificant in all the models. Consequently, the team next explored ways to potentially estimate the AADBs from the available short-term counts.

ESTIMATING AADBs FROM THE SHORT-TERM BICYCLE COUNTS

The City of Cambridge does not provide yearly bicycle count data to enable calculating AADBs for the given sites and using them for estimating AADBs for other locations. However, the city does have one permanent bicycle count station that can be used to extrapolate short-term bicycle counts to AADBs. Therefore, the research team calculated *K*-factors for the permanent bicycle count station and applied that to the other study sites.

A *K*-factor is the proportion of design hourly volume to average annual daily traffic (AADT), as defined in figure 15. In this case, the team considered the peak-hour bicycle count data.

$$K = \frac{DHV}{AADB}$$

Figure 15. Equation. Calculation based on *K*-factor and AADB.

Where:
K = the factor used for traffic volume adjustment for volume distribution in a 24-h period.
DHV = the design hourly bicycle volume for the 30th highest hourly volume for both directions.

The team considered the following steps to calculate *K*-factors for permanent bicycle counts given its raw data:

- Extracting the 2016 and 2019 permanent bicycle count data according to the dates of the study intersection.
- Adjusting the values given the adjustment factor of 1.167.(22)
- Calculating AADB by considering the number of days within each year and the number of missing days.
- Calculating two sets of *K*-factors for both dominant and nondominant directions, with 2016 and 2019 data to be further applied to the other study sites.

The research team considered each direction of travel as an independent site and calculated AADB values separately. Table 28 shows the calculated and adjusted AADBs for each direction of each year and the *K*-factors for the permanent count station data. The year 2016 was a leap year, and the analysis included this additional adjustment factor when calculating the AADB.

Table 28. Permanent Count Station *K*-factors.

Date	Direction	Time	Peak-Hour Volume	AADB	*K*-Factor
9/13/2016	Eastbound	Peak hour	79	678	0.11652
9/13/2016	Westbound (dominant)	Peak hour	224	547	0.40951
9/17/2019	Eastbound	Peak hour	77	717	0.10739
9/17/2019	Westbound (dominant)	Peak hour	207	661	0.31316

Ultimately, the team applied the calculated *K*-factors represented in table 28 to the other study sites considering the dominant direction and year. For areas with only one direction of travel for bicyclists, the team implemented the *K*-factor of the dominant direction. If both directions had the same bicycle volume, the team applied a value of 0.12367, which equals (79+224)⁄(716+661)⁄2, for 2016 and a value of 0.10305, which equals (77+207)⁄(716+661)⁄2) for 2019 for both directions.

The research team then mapped the adjusted exposure estimates to site and crash data for an assessment of safety for bicycle facilities in Cambridge.

CHAPTER 5. ESTIMATING BICYCLE EXPOSURE: SAN FRANCISCO

INTRODUCTION

For this chapter, the research team selected the San Francisco as a case study to determine the feasibility of estimating AADB values based on known counts. San Francisco has installed both permanent and temporary bicycle counters at various locations within the city. Each bicycle counter provides multiyear cyclist counts for the bicycle counter location. The research team used these count data and blended these data with additional site features collected by the research team (refer to chapter 3 for more information on data collection).

The goal of this data-merging effort was to develop a database that could be used to develop regression models that could reliably predict AADB for typical urban roadway facilities. This chapter reviews this effort, first by identifying the data collection and database development effort and then by reviewing the subsequent modeling process.

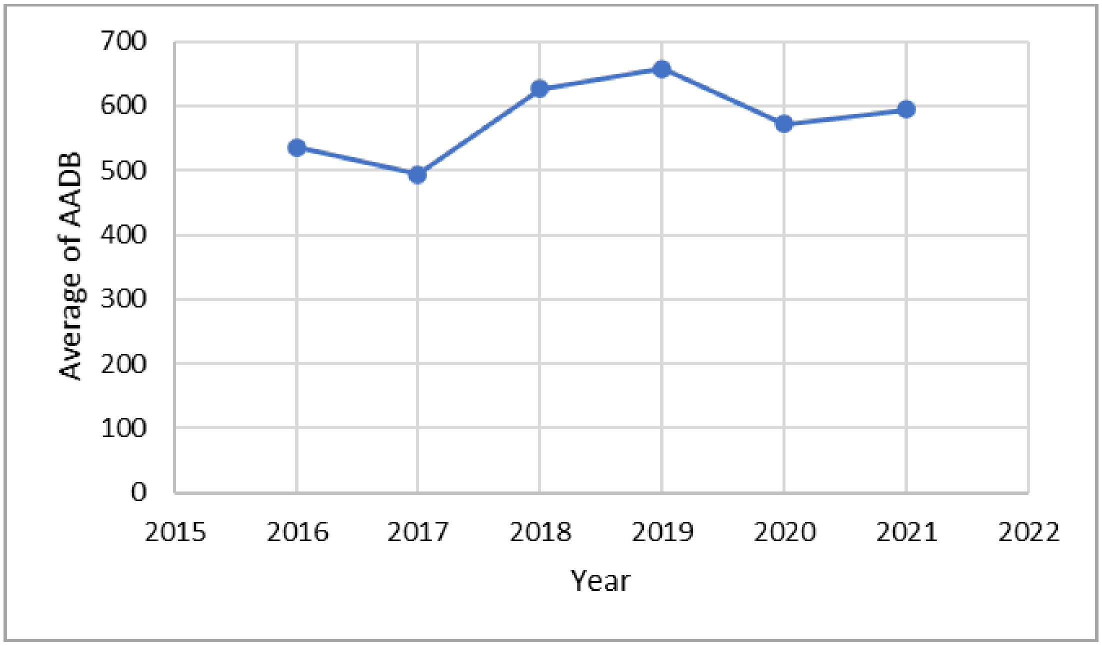
DATA COLLECTION: BICYCLE COUNT AND SITE FEATURE VARIABLES

The team obtained San Francisco bicycle count data from the San Francisco Municipal Transportation Agency website.(25) The data collection covered the period from 2016 to 2021 and included data from 1 to 5 yr, depending on the availability at each site. Table 29 provides the distribution of the bicycle count data for each year.

Table 29. Distribution of bicycle count data over years for San Francisco.

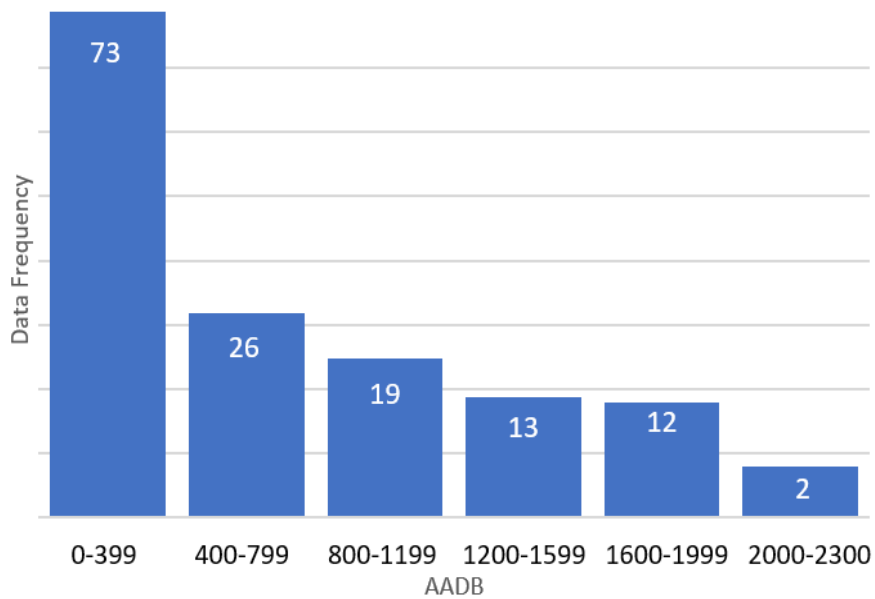
Year	Frequency
2016	32 (leap year)
2017	32
2018	26
2019	24
2020	20 (leap year)
2021	11
Total	145

The bicycle count data represent the total number of bicyclists over each year for each site. To calculate the AADB for each individual site and year, the number of days per year should be considered (because years divisible by four are leap years). Figure 16 depicts the AADB over the sites for each year. The drop in the AADB starting in 2020 might be associated with the pandemic. Therefore, to avoid any bias in the results due to the pandemic, the team removed the 31 data points for 2020 and 2021. Figure 17 represents a graphical distribution of the AADB values for the study sites after removing the 2020 and 2021 data.



Source: FHWA.

Figure 16. Graph. Average AADB for San Francisco (2016–2021).



Source: FHWA.

Figure 17. Chart. AADB distribution for San Francisco (2016–2019).

The sites located in the study region represent a variety of bicycle facilities. Table 30 summarizes the bicycle facilities as identified by the data collection efforts.

Table 30. Frequency of various types of bicycle facilities for San Francisco.

Bicycle Facility Type	Frequency (No.)
Nothing	34
Painted bicycle lane: no buffer	36
Painted bicycle lane: with buffer	6
SBL: with buffer	38
Total	145

For further statistical analysis and modeling, the research team assembled various roadway and site characteristic variables to evaluate as surrogates for AADB. Table 31 identifies and defines these study variables, and table 32 provides the descriptive statistics for the variables.

Table 31. Study variables for San Francisco.

Variable	Definition
Length (mi) of bicycle lanes within 1 mi	Length (mi) of bicycle lanes within 1 mi radius of a bicycle counter
ADT	ADT (vehicle/day)
Population density	Population density (people/mi^2)
One-way roadway	Whether a roadway is one-way
Presence of bicycle lane	Whether a bicycle lane exists at the count location
Residential binary	Whether the adjacent land use is residential
Continuous bicycle lane	Whether the adjacent bicycle lane is continuous

Table 32. Descriptive statistics for the study variables for San Francisco.

Variable	Mean	Standard Deviation	Minimum	Maximum
AADB	570.76	546.79	39	2,137
ADT	12,512.84	6,142.11	0	24,110
Population density	24,010.02	10,247.75	175	46,570
Continuous bicycle lane	0.70	0.46	0	1
One-way roadway	0.21	0.41	0	1
Residential binary	0.33	0.47	0	1
Length (mi) of bicycle lanes within 1 mi	8.26	5.21	0.15	16.55
Presence of bicycle lane	0.72	0.45	0	1

The team considered *Land Use* as another variable in the AADB analysis. Most of the adjacent land use is residential, whereas commercial, industrial, public, and mixed use are sparsely distributed within the study region of the city.

PRELIMINARY STATISTICAL ASSESSMENT: CORRELATION TEST

As an initial step, the research team conducted a correlation test to assess correlation between the individual variables. Table 33 presents the results of the Pearson's correlation test. None of the variables are highly correlated. Therefore, there was no need to consider including any interaction terms in the prediction models.

Table 33. Correlation test for San Francisco.

Variable	ADT	Log(ADT)	Population Density	Residential Binary	One-Way Roadway	Length (mi) of Bicycle Lanes Within 1 Mi	Presence of Bicycle Lane
ADT	***1***	—	—	—	—	—	—
Log(ADT)	0.66	***1***	—	—	—	—	—
Population density	–0.11	–0.11	***1***	—	—	—	—
Residential binary	–0.14	–0.25	0.16	***1***	—	—	—
One-way roadway	0.04	0.11	0.20	–0.09	***1***	—	—
Length (mi) of bicycle lanes within 1 mi	0.10	0.30	0.38	–0.31	0.26	***1***	—
Presence of bicycle lane	0.21	0.33	0.06	–0.06	0.13	0.21	***1***

MODELING RESULTS FOR SAN FRANCISCO

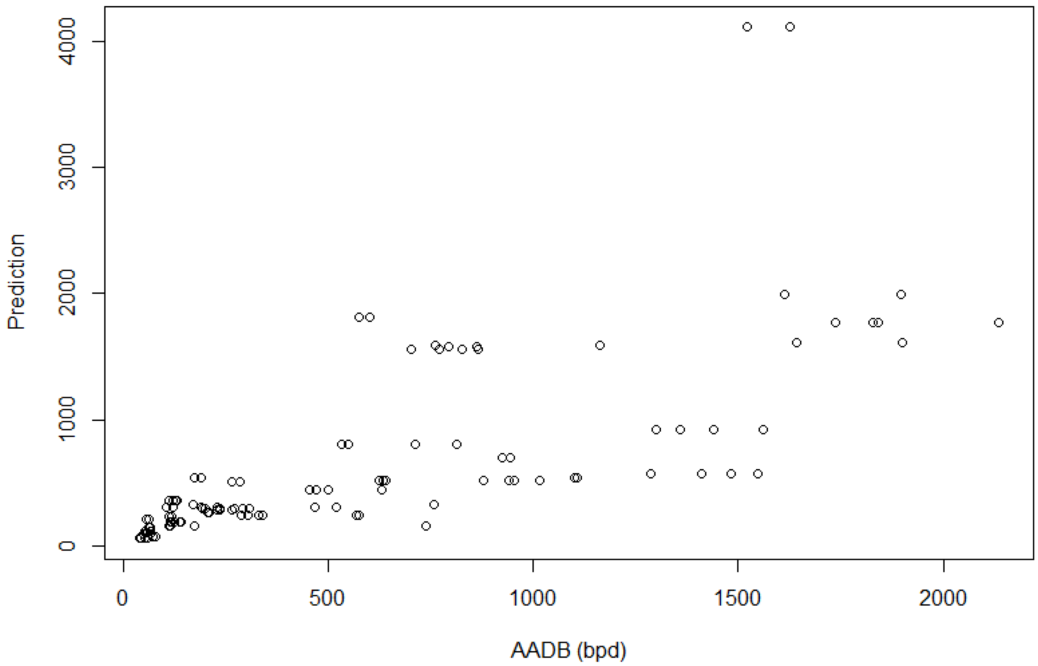
The research team examined various statistical techniques and explored a combination of the study variables to develop the AADB prediction models. Ultimately, among the developed models, the research team determined that the Poisson mixed–effect model represented in table 34 and figure 18 provided the best prediction. In this model, AADB is the dependent variable, site number is the random-effect variable, and log(ADT), miles of bicycle lanes within 1 mi, population density, one-way roadway, and land use are considered independent variables. Table 34 depicts the cumulative residual plot based on miles of bicycle lane with 1 mi. similarly depicts the cumulative residual plot based on ADT.

Table 34 further demonstrates that an increasing log(ADT), population density, miles of bicycle lanes within 1 mi, and consideration of providing one-way roadways were associated with an increase in the expected AADB). Moreover, providing mixed-use, public, and residential land uses appeared to be associated with a decrease in the number of bicyclists compared to the commercial and industrial land uses.

Table 34. Final bicycle surrogate model for San Francisco.

Variable	Estimate	Standard Error	*z*-Value	*Pr*(>|*z*|)
(Intercept)	4.668	0.481	9.699	<0.0001
Length (mi) of bicycle lanes within 1	0.094	0.020	4.672	<0.0001
Factor(one-way roadway)	0.813	0.206	3.951	<0.0001
Log(ADT)	0.089	0.047	1.899	0.0576
Population density/1,000	0.017	0.009	1.933	0.0533
factor(NewLU) mixed use*	−1.104	0.222	−4.965	<0.0001
factor(NewLU)public	−1.555	0.326	−4.765	<0.0001
factor(NewLU)residential	−1.354	0.232	−5.835	<0.0001

Functional form: AADB ~ log(ADT) + Length (mi) of Bicycle Lanes Within 1 Mi + Population Density/1,000 + factor(One-Way Roadway) + factor(NewLU) + (1 | Location).
*Base scenario: commercial and industrial.
LU = land use; *Pr* = probability.
Note: Akaike information criterion (AIC) = 1,934.2; deviance = 1,916.2; random-effect variance = 0.3491; average prediction error = 284.77; coefficient of variation (CV) = 0.499.



Source: FHWA.
bpd = bicycles per day.

Figure 18. Graph. Scatterplot for San Francisco model.

CHAPTER 6. ESTIMATING BICYCLE EXPOSURE: SEATTLE

INTRODUCTION

This chapter summarizes the bicycle exposure modeling process for Seattle. The research team selected Seattle as a case study to determine the feasibility of estimating AADB values based on known counts. Seattle has installed both permanent and temporary bicycle counters at various locations within the city. Each bicycle counter provides multiyear cyclist counts for the bicycle counter location. The research team blended these count data with additional site features collected by the research team. The goal of this data-merging effort was to develop regression models that could reliably predict AADB for typical urban roadway facilities. This chapter reviews this effort, first by identifying the data collection and database development effort and then by reviewing the subsequent modeling process.

DATA COLLECTION: BICYCLE COUNT

The research team assembled a variety of roadway and site features to determine reasonable site features that might serve as surrogates for AADB. Because the goal of this effort was to base the predictive method on actual bicycle volume information, where possible, the team acquired bicycle count data that were previously collected from Seattle.(27) The team then used these bicycle count data to calculate the respective AADB values for each count station location. The City of Seattle installed 12 bicycle counters within the city, and the data from 10 of the counters are publicly available.

Among the 10 bicycle counters for which data were readily available, 3 were permanent counters that monitored cyclists 24 h/d, 7 d/w, and 365 d/yr. The City of Seattle uploads the data from these three counters once a day. The city uploads the data for the remaining seven counters once a month. The data acquired from these bicycle counters date back to 2014. Based on the reporting frequency of the data and the available number of months and days for each counter (and adjusting for some missing days or months), the research team calculated the AADB for each year at each site. Table 35 shows the sites and the number of available years of data.

Table 35. Bicycle counters and number of available years of data.

Bicycle Counter Name	Count at Site
2nd Ave Bicycle Counter	*5*
39th Ave NE Greenway at NE 62nd St	4
Broadway Cycle Track North of E Union St	6
Burke Gilman Trail North of NE 70th St	6
Chief Sealth Trail North of Thistle	2
Elliott Bay Trail in Myrtle Edwards Park	7
Fremont Bicycle Counters	*7*
MTS Trail West of I-90 Bridge	7
NW 58th St Greenway at 22nd Ave NW	7
Spokane Bicycle Counters	*7*
Total	58

Note: The italicized cells indicate the permanent counters.

The team members eliminated nine data points that collectively represented two bicycle trails from further analysis because of the different characteristics of bicycle trails compared to on-street bicycle facilities. Ultimately, the bicycle count database included 49 observations available for further analysis.

DATA COLLECTION: SITE FEATURES

In addition to the acquisition of actual bicycle count data, the research team also compiled a database that included on-road bicycle facilities (primarily traditional bicycle lanes, bicycle buffers, and SBLs). For each of these facilities, team members documented a variety of site characteristics that could potentially influence the route choice and resulting roadway facility bicycle volume. The following eight variables introduce features assembled in the site feature database for which the variables appeared to have some potential correlation to the AADT (or ADT), as observed during the subsequent statistical modeling efforts:

- ADT: The research team obtained the annual ADT data from the Washington Geospatial Open Data Portal.(28) The available data date back to 2014.

- Presence of bicycle lane: Team members collected this variable from aerial views. The variable is a binary value and indicates whether a bicycle lane exists, regardless of the facility type.

- New land use: The researchers combined the single-family and multifamily residentials to represent “Residential” as a single category. This information was acquired by examining the land use through a street view perspective on a Web mapping platform.

- Residential binary: Team members downloaded land-use data from the Washington Geospatial Open Data Portal and converted this information to a binary variable to indicate whether the dominant land use near a bicycle counter was residential.(27)

- Population density: The team acquired population and area (m^2) data from a free on-line data source. These data provided information at the census tract level.(25) This information includes the population density (population/mi^2) for each census tract.

- Length of bicycle lanes within 1 mi of the bicycle counters: The research team determined the bicycle facilities within Seattle using an online mapping platform. The team then imported the data to a geospatial mapping system drew buffers with 1-mi radii around each bicycle counter. Eventually, the team measured the length of bicycle miles within each buffer. Each direction of travel was considered separately in the measurements.

- Bicycle lane continuity: Team members developed this variable from an aerial view to indicate whether a counter is located on a roadway with a continuous bicycle facility (i.e., the bicycle lane does not stop and start as a result of adjacent development).

- One-way roadway: Team members used Google Earth aerial views to determine whether the roadway of interest operated as a one-way facility.

Table 36 through table 38 summarize the study variables.

Table 36. Frequency of different bicycle facilities.

Bicycle Facility	Count
None	38
SBL	11
Total	49

Table 37. Frequency of different land-use categories.

Land Use	Count
Commercial/mixed use	6
Downtown	5
Manufacturing/industrial	14
Multifamily	13
Single family	11
Total	49

Table 38. Descriptive statistics of the numerical study variables.

Variable	Mean	Standard Deviation	Minimum	Maximum
AADB	872.31	836.50	94	3,259
Population density	12,111.94	9,323.02	2,439	32,933
Presence of bicycle lane (1 = yes)	0.22	0.42	0	1
One-way roadway	0.10	0.31	0	1
ADT	12,510.73	8,703.73	6,300	31,855
Continuous bicycle lane	0.22	0.42	0	1
Residential (1 = yes)	0.49	0.51	0	1
Length (mi) of bicycle lanes within 1 mi of the bicycle counters	6.13	5.30	0.28	15.232

The 2020 AADB decreased consistently for all study sites with available data. Most likely, this observed change in bicycle operations was associated with changes in traffic patterns resulting from the 2020 pandemic. Therefore, for the subsequent statistical analysis, the variable *Year* has been considered in the modeling process to evaluate the models for any annual significance.

PRELIMINARY STATISTICAL ASSESSMENT: CORRELATION TEST

An initial way to assess the potential influence of roadway features and their relationship to the AADB is to determine how the individual variables may be correlated. Table 39 shows the Pearson's correlation coefficient test between the numerical variables. The italicized cells in table 39 indicate variables that are highly correlated (with values approaching 1.0). For these variables, an inclusion term to capture the interaction between variables should be considered if both variables are retained in a model.

Table 39. Correlation test for Seattle.

Variable	ADT	Population Density	Presence of Bicycle Lane	Residential Binary	Continuous Bicycle Lane	One-Way Road	Length (mi) of Bicycle Lanes Within 1 Mi of the Counter
ADT	***1***	—	—	—	—	—	—
Population density	0.06	***1***	—	—	—	—	—
Presence of bicycle lane	–0.09	***0.76***	***1***	—	—	—	—
Residential binary	–0.50	–0.48	–0.54	***1***	—	—	—
Continuous bicycle lane	–0.09	***0.76***	***1.00***	–0.54	***1***	—	—
One-way road	0.20	0.08	0.58	–0.32	0.58	***1***	—
Length (mi) of bicycle lanes within 1 mi of the counter	–0.04	***0.82***	***0.91***	–0.48	***0.91***	0.55	***1***

Note: The italicized cells indicate variables that are highly correlated (with values greater than 0.7).

MODELING RESULTS

The research team explored a variety of statistical techniques for the development of AADB predictive models. Ultimately, the research team determined that a mixed-effect Gaussian model that used the log(AADB) as the dependent variable and the site number as a random-effect variable provided the best predictive fit for the model. The following summary provides an overview of this mixed-effect Gaussian process model.

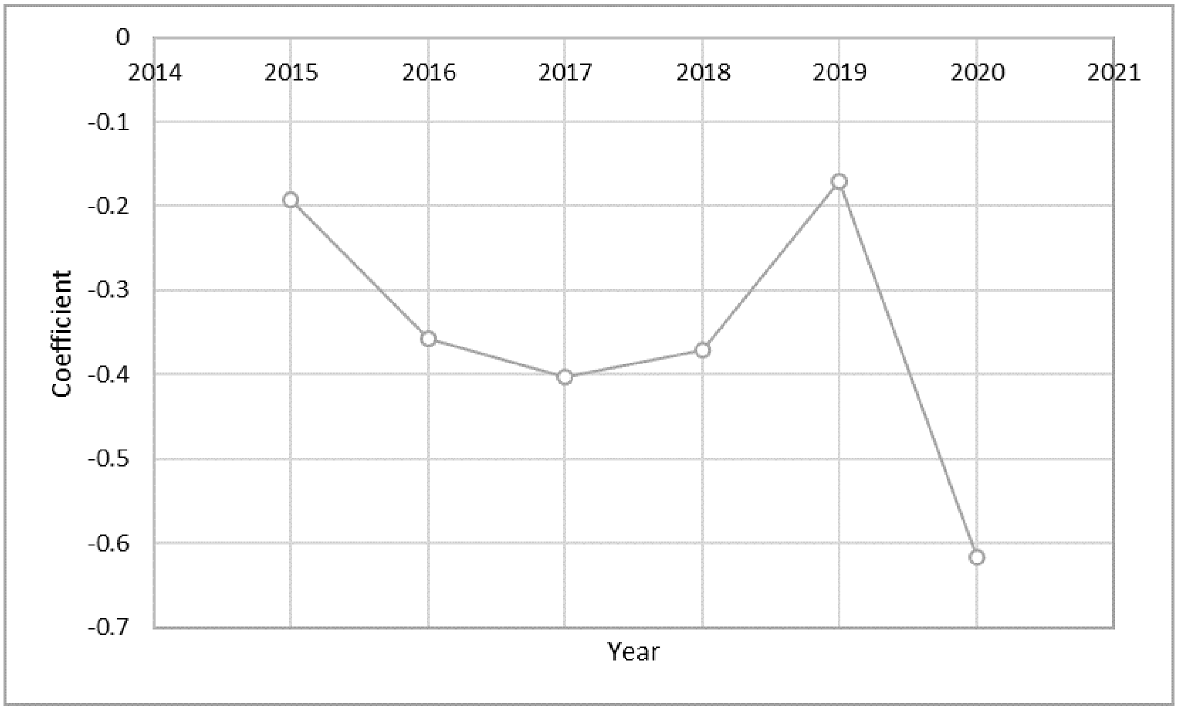
As an initial step, the research team evaluated a combination of several study variables to achieve a reasonable model to predict AADB. The initial mixed-effect Gaussian model included all the years of data, including the pandemic year of 2020 (table 40).

Table 40. Mixed-effect Gaussian model, including 2020 data.

Parameter	Estimate	Standard Error	df	*t*-Value	*Pr*(>|*t*|)
(Intercept)	−6.898	2.644	6.173	−2.609	0.03915
Log(ADT)	1.461	0.286	6.173	5.114	0.002
Factor(Year)2015	−0.192	0.147	35.046	−1.311	0.198
Factor(Year)2016	−0.357	0.143	35.107	−2.501	0.017
Factor(Year)2017	−0.403	0.143	35.107	−2.823	0.008
Factor(Year)2018	−0.371	0.149	35.211	−2.489	0.018
Factor(Year)2019	−0.171	0.149	35.211	−1.151	0.257
Factor(Year)2020	−0.617	0.166	35.449	−3.715	0.0007

Functional form: log(AADB) ~ log(ADT) + factor(Year) + (1 | Site).
df = degrees of freedom.
Note: Random effect variance = 0.188.

Based on these initial modeling results, the value of log(AADB) increases by increasing the log(ADT). The model used 2014 as a base year. The number of bicycles decreased for all the years compared to the 2014 base year scenario. In addition, a substantial drop in the coefficient for the *Year* variable for the pandemic year of 2020 was also notable. This observation is graphically depicted in figure 19. Based on these observations, the research team then removed the 2020 data points from further analysis. This observation is also important because it indicates that an analysis based solely on traffic counts from 2020 cannot be expected to provide reliable results when contrasted with bicycle volume information from the most recent years before the pandemic.



Source: FHWA.

Figure 19. Graph. Change in the Seattle coefficients of variable *Year* for consecutive years.

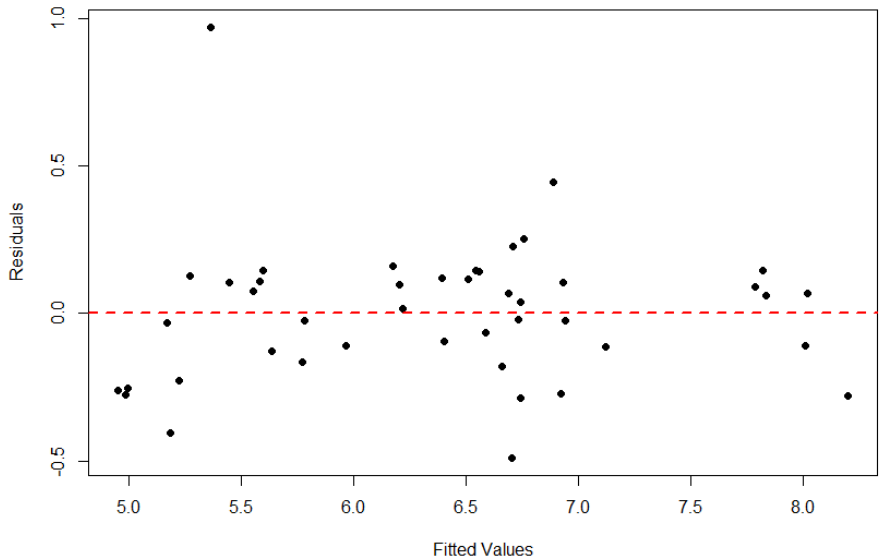
After removing five observations that represented the 2020 data, the team members developed another regression model. The results are shown in table 41. As shown in figure 19, a negative coefficient suggests a decrease in the volume and an increase in coefficient suggests an increase in volume. During 2020, the bicycle usage trends changed significantly. This observation suggests that a model without 2020 data may be needed. Additionally, figure 20 depicts the residual plot of the model. As provided, an increase in the log(ADT) is similarly associated with an increase in the log(AADB). The data showed significantly fewer bicycles for 2016–2018 than in 2014, whereas 2015 and 2019 data did not show a significant relationship when compared to the AADB.

Table 41. Mixed-effect Gaussian model excluding 2020 data.

Parameter	Estimate	Standard Error	df	*t*-Value	*Pr*(>|*t*|)
(Intercept)	−6.797	2.513	6.016	−2.705	0.035
Log(ADT)	1.452	0.272	6.020	5.344	0.002
Factor(Year)2015	−0.192	0.151	31.035	−1.274	0.212
Factor(Year)2016	−0.367	0.147	31.129	−2.491	0.018
Factor(Year)2017	−0.413	0.147	31.129	−2.804	0.009
Factor(Year)2018	−0.380	0.153	31.238	−2.476	0.019
Factor(Year)2019	−0.181	0.153	31.238	−1.179	0.247

Functional form: log(AADB) ~ log(ADT) + factor(Year) + (1 | Site).

Note: Random effect variance = 0.1643; residual variance = 0.07965; restricted maximum likelihood (REML) = 40.8.



Source: FHWA.

Figure 20. Graph. Seattle residual plot for model 1 where the dashed line represents the mean of observations and the dots represent the individual observations.

The research team developed a new variable referred to as *New Year* because the data from years 2015 and 2019 were not significant in the model compared to the 2014 base year condition. If the year of interest was either 2014, 2015, or 2019, then the value of *New Year* was equal to one. Values for *New Year* for other years had a value of zero. This difference in past years will introduce a challenge when trying to use the model to predict future years. However, this model does represent the best performing model, but future model evaluations should assess the sensitivity of this year-based variable and how it influences predictive capabilities beyond the 2014–2020 study period. For the current model, the analysts replaced the variable *Year* with *New Year* and added new variables. This change resulted in the final model that is presented in table 42.

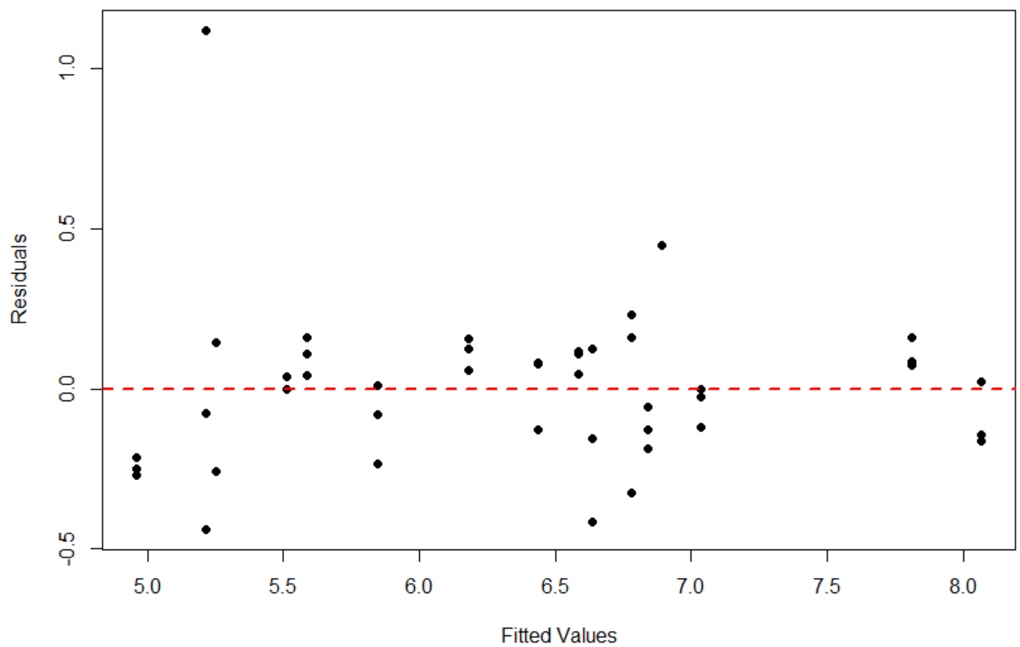
As indicated, an increase in the log(ADT) is associated with a significant increase in the number of bicycles. Moreover, the variable *New Year* shows that the AADB significantly decreased during 2016–2018 compared to 2014, 2015, and 2019. Additionally, providing a bicycle lane and increasing the population density corresponded to a significant reduction in the AADB value; however, the positive sign of the interaction term between the presence of a bicycle lane and population density should not be neglected.

Table 42. Mixed-effect Gaussian model excluding 2020 data and using *New Year*.

Variable	Estimate	Standard Error	df	*t*-Value	*Pr*(>|*t*|)
(Intercept)	−10.021	2.221	3.051	−4.513	0.020
Log(ADT)	1.827	0.250	3.044	7.321	0.005
Presence of bicycle lane	−1.896	0.812	3.206	−2.337	0.096
Population density/1,000	−0.069	0.028	3.002	−2.474	0.090
Factor(New Year)1	0.257	0.084	35.068	3.075	0.004
Presence of bicycle lane: population density/1,000	0.115	0.044	3.076	2.632	0.076

Functional form: log(AADB) ~ log(ADT) + Presence of Bicycle Lane + Population Density/1,000 + Presence of Bicycle Lane × Population Density/1,000 + factor(New Year) + (1 | Site).
Note: Random effect variance = 0.08396; residual variance = 0.07534; REML = 39.3.

Figure 21 depicts the residual plot model 1 where the dashed line represents the mean of observations and the dots represent the individual observations.



Source: FHWA.

Figure 21. Graph. Residual plot for Seattle model 2 where the dashed line represents the mean of observations and the dots represent the individual observations for the *New Year* variable (Seattle model 2).

Based on this analysis, the best predictive model is shown in table 42 and represented by figure 22. The research identified this model as the most reliable model that could be implemented to estimate the AADB based on ADT, *New Year* variables, presence of bicycle lane, and population density.

$$
\begin{aligned}
AADB = Exp(&-10.021 + 1.827 \times \ log(ADT) + 0.257 \times New\,Year \\
&- 1.896 \times Presence\ of\ Bicycle\ Lane - 0.069 \times \frac{Population\ Density}{1{,}000} \\
&+ 0.115 \times Presence\ of\ Bicycle\ Lane \times \frac{Population\ Density}{1{,}000})
\end{aligned}
$$

Figure 22. Equation. Seattle bicycle exposure prediction.

Where:

New Year = 1 if predicting for 2014, 2015, or 2019 (otherwise zero).
Presence of bicycle lane = 1 if a bicycle lane is present (otherwise zero).
Population density = census tract population density (population/mi^2).

CHAPTER 7. DEVELOPMENT AND TESTING OF SBL CMFs

INTRODUCTION

The goal of this research effort was to determine whether a reliable CMF could be developed for SBL facilities. As documented in the previous chapters of this report, the research team developed a data collection procedure and then conducted data collection using aerial photography, the Street View features of Google Maps, and database information that could be acquired for the study sites. Because the team could not physically collect the data (due to the pandemic restricting travel), the research team developed bicycle exposure models to represent bicycle volumes for the study sites. This CMF development included data from Cambridge; San Francisco; and Seattle. The project team also acquired data for Austin, and Denver, for ultimate transferability testing of the CMFs. This chapter reviews the CMF development for SBLs.

STUDY DESIGN

Cross-Sectional Analysis

The following two basic designs for observational studies are frequently used in safety evaluations:

- Cross sectional.
- Before and after (longitudinal).

The research team pursued a cross-sectional design after identifying the potential data sources, their strengths and limitations, and the challenges to collect key variables for a before–after evaluation. Particularly, a longitudinal (before–after) design requires knowledge of the date of conversion for the studied facilities extending from any prior condition to when the SBL or other conditions were implemented. These detailed longitudinal data were not available for this study. Additionally, a longitudinal study is generally characterized by the risk of a smaller dataset, considering that no guaranties of finding sufficient locations with the exact prior condition that were converted to SBL with the same characteristics existed. Finally, a before–after longitudinal analysis can suffer from site selection bias because treatments are typically implemented at the locations with the greatest need. Therefore, the team selected a cross-sectional analysis that allowed the team to develop larger datasets for the cities under study.

Good observational studies rely on data from sites with and without the study treatment, and the data should be assembled in a manner consistent with control-group experiments. To obtain sufficient data to develop CMFs for SBL facilities, the research team obtained data for locations with SBL facilities and roadways that featured bicycle lanes without SBLs. This approach strengthens the analysis by enabling base condition evaluations (bicycle lane with no offset) as well as SBLs with additional enhancements. For this study, the best base condition should most likely be sites with traditional bicycle lanes, because the vast majority of on-street bicycle facilities are traditional configurations. The target configuration would then be SBLs with varying vertical elements.

Balancing Covariates with Propensity Score (PS) Methods

Data-matching and data-balancing methods are used to assist causal inference that quantifies the impact of a treatment on a response variable (crashes in this case). The principle behind these methods is to ensure that untreated locations (i.e., no SBL present) are similar in their safety-relevant covariates (e.g., AADT, average daily bicycle traffic (ADBT), number of lanes) at the treated locations (i.e., SBL present) in a way that the contrast between the two groups of sites is balanced. In that case, the comparison between the two groups of sites should reflect safety differences due to the treatment of interest.

The PS is a metric of similarity between covariates from the cases and can be estimated using parametric or nonparametric tools, such as logistic regression or random forest analysis.

In the case of binary logistic regression, used as a basis for PS estimation, figure 23 shows the definition of the conditional probability of a site receiving treatment *T*.

$$P(T_i|X_i) = \frac{e^{\alpha_i X_i}}{1 + e^{\alpha_i X_i}}$$

Figure 23. Equation. Probability equation.

Where:

$P(T_i|X_i)$ = the PS denoting the probability of the site i receiving the treatment T.
T_i = the treatment status of the site i which takes binary values {0, 1}.
X_i = a vector of covariates that covary with the treatment presence.
α_i = the vector of coefficients through the binary logistic regression.

In a balanced sample, the distribution of PSs is expected to be similar for treated sites $P(T_A|X_A)$ and comparison sites $P(T_B|X_B)$. PS matching consists of using some form of PS to inform the selection of the data for a study. Alternatively, PS weighting (PSW) consists of using weights in the analysis to balance two or more partitions of the data by the variable of interest (i.e., treatment or comparison). Balance is achieved by defining appropriate weights for each unit of analysis so that they represent an underlying target population of sites. The data are weighted based on the probabilities of being in either the comparison or treatment group.(29) The definition of the weights selected implies a target population of sites. If all weights are equal, then the dataset is implied to be a simple random sample from an actual population of sites. However, through the use of appropriate weights, more flexible definitions of the target population are possible, as can be found in the statistical literature.(24,30)

The research team set the target population in this study as the overlap between the treated and comparison populations as proposed by Li, Morgan, and Zaslavsky.[31] For this scheme, the target population is the set of all sites that have comparable chances to be either in the treatment group or in the comparison group. This approach effectively curbs the undue influence of two subsets of sites when estimating the average treatment effect of the countermeasure:

- Comparison sites with characteristics that make the sites unlikely to be candidates for the treatment.

- Treated sites with unusual characteristics for which no comparable comparison sites are represented in the data.

An additional advantage of this choice of target population is a desirable small-sample exact balance property. Additionally, the corresponding weights are known to minimize the asymptotic variance of the weighted average treatment effect within their class of weights.[31]

DATA ANALYSIS METHODS

The research team explored the use of various appropriate generalized linear model (GLM) specifications (negative binomial, binomial, or binomial mixtures) as needed by each dataset. PSW was implemented using the PSs obtained from the final datasets.

GLM methods define an appropriate link function to articulate the relationship between the response variable distribution (crashes in this case), such as Poisson or negative binomial, and the linear function of explanatory variables in the analysis.

The research team found the number of bicycle crashes to be very small, so they applied binomial GLMs to the data after aggregating the crash data to a total count for the complete period of analysis. In this instance, the distribution of a response variable *Y,* indicating the number of success observations from a binomial trial (regardless of whether a crash of interest has occurred), can be modeled conditional to a set of independent variables *X,* as shown in figure 24.

$$P(Y = y_i | X_i, Segment_i) = \binom{n_i}{y_i} \cdot p^{y_i} \cdot (1 - p)^{n_i - y_i}$$

Figure 24. Equation. Conditional probability of *Y* value, given explanatory variables and site characteristics.

Where:

P = the probability of Y taking value y_i, given the ith realization of a set of explanatory variables X.

Y = the count of observed crashes of interest, given n trials.

y_i = a particular value in the domain of random count variable Y.

n_i = the reference number of trials for which Y is observed.

P_i = the probability of a crash in the ith location of interest.

For a crash study site i, the logit of pi can be expressed as in figure 25.

$$g(p_i) = \ln\left(\frac{p_i}{1-p_i}\right) = \beta' \cdot X_i$$

Figure 25. Equation. Binomial-lognormal mixed-model parameterization.

Where:

$g(p_i)$ = the logit function of p_i.
p_i = the probability of ith segment.
X = the vector of independent variables (including key variable in evaluation and other safety-influential covariates).
β = the vector of regression coefficients.

All model variables were included in the model, either in the exponential form or directly, depending on the best fit to each dataset. For clarity, the last term in figure 25 is implicit of multiple variables and can be expanded as in figure 26.

$$\boldsymbol{X}' \cdot \boldsymbol{\beta} = X_1 \cdot \beta_1 + X_2 \cdot \beta_2 + \cdots + X_{\boldsymbol{p}} \cdot \beta_p$$

Figure 26. Equation. Parameterization of explanatory variables in regression model.

Where:

X_p = an independent variable in the model, such as AADT, ADBT, the number of lanes, etc.
β_p = the corresponding estimated coefficient.

CMF Estimation

In most cases, the use of regression models to estimate the influence of a dependent variable consists of extracting a single parameter estimate and its standard error from the analysis after accounting for additional variability in the data due to covariates and an appropriately modeled error distribution. However, single-parameter estimation is not possible in every case and, in particular for this study, where the estimation often involved contrasting more than one coefficient with each other. To estimate the uncertainty of a CMF derived from multiple coefficient contrasts, the research team followed CMF development procedures of which the basis of these methods is the asymptotically multivariate normal distribution expected from maximum-likelihood estimation of multiple variable regression models.[32–34]

For this procedure, the analyst defines appropriate linear combinations of the coefficient estimates from each of the best models to statistically assess their resulting value for select scenarios. These linear combinations imply predicted crashes for both the before condition (e.g., no SBL and some base condition) and the after condition (e.g., SBL present or type of SBL). The contrast between these conditions then yields an estimate of the CMF of interest. In general, producing the CMF estimate for the scenario is straightforward. To produce the corresponding standard error for a given scenario with covariate vectors *XB* and *XA* representing the before and after conditions, respectively, the contrast of covariate vectors and the maximum likelihood model-inversed-information matrix ∑ define the CMF standard error, as indicated in figure 27.

$$SE(\log CMF) = \sqrt{(X_A' - X_B') \times \Sigma \times (X_A - X_B)}$$

Figure 27. Equation. Standard error for contrast in log scale.

Where:

SE = represents the calculated model standard error.
CMF = the crash modification factor to be developed.
X_A *and* X'_A are the values after an intervention, such as crash results after constructing intervention such as an SBL.
X_B *and* X'_B are the values before an intervention, such as crash results before constructing intervention such as an SBL
X_p = an independent variable in the model, such as AADT, ADBT, the number of lanes, etc.
∑ = summation of the model effects.

Contrasts of Interest for CMF Development

For this research, the team members constructed contrasts representing a progression of information to be gathered in the form of CMFs. The analysis included the following steps:

1. In the first hierarchical level, the team developed models that allowed them to test research questions involving sites with any type of SBL and other sites without SBLs. Depending on the data available, multiple contrasts were constructed at this hierarchical level:

    a. SBL versus traditional bicycle lane.

    b. SBL versus buffered bicycle lane.

    c. Buffered versus traditional bicycle lane.

2. In the second hierarchical level, the team expanded the models to allow testing differences between sites with specific types of SBLs and other sites without SBLs. Again, data availability determined which of the following contrasts were available for estimation in each case:

    a. Flexi-post SBL versus traditional bicycle lane.

    b. Flexi-post SBL versus buffered bicycle lane.

    c. Flexi-post SBL versus traditional or buffered bicycle lane.

    d. Blended type SBL versus traditional bicycle lane.

    e. Blended type SBL versus buffered bicycle lane.

f. Blended type SBL versus traditional or buffered bicycle lane.

g. Flexi-post SBL versus blended type SBL.

h. Flexi-post SBL or blended type SBL versus traditional bicycle lane.

i. Flexi-post SBL or blended type SBL versus buffered bicycle lane.

j. Flexi-post SBL or blended type SBL versus traditional or buffered bicycle lane.

All analyses were conducted using open-source programming software for statistical computing and graphics.

SEGMENT ANALYSIS RESULTS

The analyses used bicycle crashes as the response variable. As previously noted, the data from three cities, listed in the order in which the analysis was conducted, were used in this effort: San Francisco, Cambridge, and Seattle. For each city, the data were separated in two subsets: segments and intersections. The following sections document analyses and results, first by the different city datasets developed for this research and then as a combined dataset. The research team did not successfully develop CMFs for intersections or corridors with SBLs.

San Francisco Segment Analysis

Table 43 shows the number of segments with bicycle lane characteristics per direction of travel.

Table 43. Number of segments by bicycle lane type per direction in San Francisco (*N* = 384).

Variable	Bicycle Lane (Direction 2)	Buffered (Direction 2)	Vertical Element (Direction 2)
Bicycle lane (direction 1)	266	5	9
Buffered (direction 1)	4	45	10
Vertical element (direction 1)	7	10	28

Table 44 shows the results for the most parsimonious model of potential bicycle crashes, when considering only contrasts that involve any type of SBL. The research team adjusted up (i.e., increased) the estimated standard errors via the quasi-likelihood estimation method to capture the increased uncertainty implied by overdispersion because they found binomial overdispersion in the residuals of this model.

Table 44. Initial model coefficient estimates for potential bicycle crashes in San Francisco (*N* = 384 segments).

Parameter	Estimate	Standard Error	*t*-value	*Pr*(>|*t*|)	Significance
(Intercept)	2.761	2.6572	1.039	0.299	—
Industrial land use	−0.605	0.3817	−1.586	0.114	—
Mixed land use	1.781	0.5794	3.075	0.002	**
Public land	−0.824	0.8977	−0.917	0.360	—
Residential	0.870	0.6626	1.314	0.190	—
Log(Length)	−1.089	0.4930	−2.208	0.028	*
Length	0.002	0.0010	2.202	0.028	*
One MV lane in each direction	−0.027	0.3046	−0.088	0.930	—
Two MV lanes in each direction	0.530	0.2686	1.974	0.049	*
No parking in one or both directions	−0.666	0.2808	−2.370	0.018	*
Area bicycle = 1	0.108	0.1964	0.550	0.583	—
Area bicycle = 2	1.125	0.3457	3.255	0.001	**
log (AADB+0.5)	−0.559	0.1767	−3.167	0.002	**
AADB	0.011	0.0027	4.130	<0.001	***
Traditional bicycle lane (both directions)	0.254	0.4317	0.589	0.556	—
Buffered bicycle lane (both directions)	0.197	0.5127	0.383	0.702	—
SBL (either direction)	−0.479	0.4951	−0.968	0.334	—

—Not statistically significant.
*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
***Statistically significant at the 0.001 level.

In general, the results in table 44 indicate the following factors:

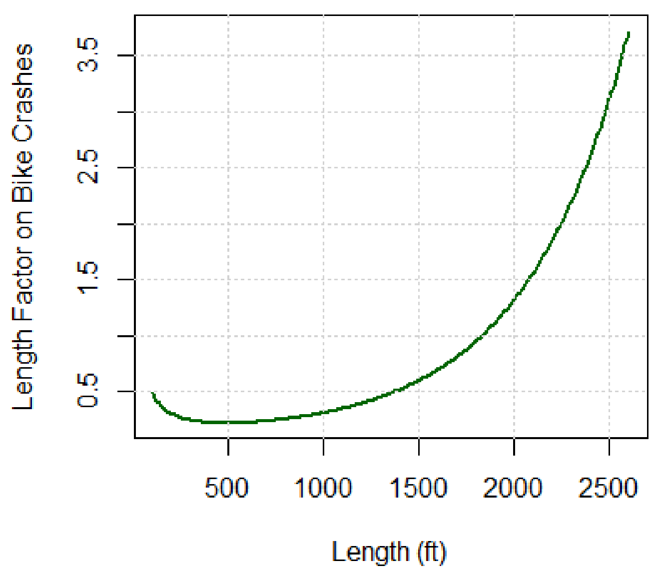
- Bicycle crash risk increases at mixed land-use locations and potentially decreases at industrial land use, compared to other location types.
- Bicycle crash risk increases at locations with two MV lanes per direction, compared to locations with more MV lanes per direction.

- Bicycle crashes decrease where no parking is permitted in one or both directions of travel. This analysis estimated that bicycle crash risk at segments with no parking on either side is about half as large as for segments allowing parking, other things being equal (0.514 odds ratio estimated as 0.514 = exp(–0.666)).

- Bicycle crash risk increases at locations where *Area Bicycle* has a 2.0 value (meaning two directions where bicycle lanes are parallel and adjacent to the segment of analysis). This value could be a surrogate indicator of bicycle travel exposure, in addition to the AADB estimated values.

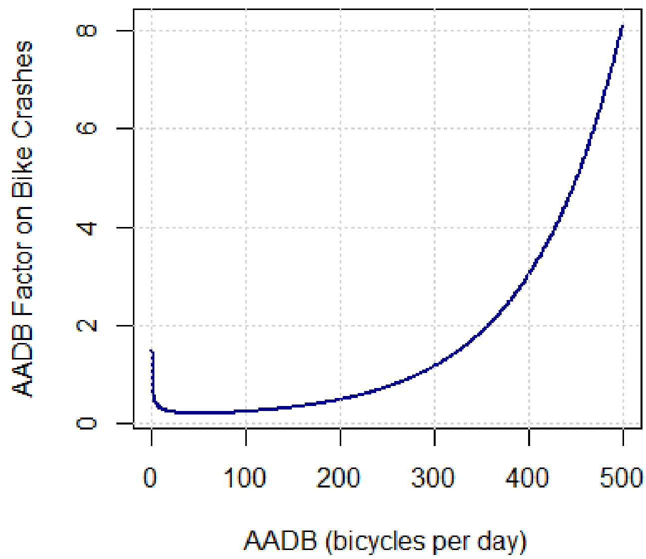
- In the cases of segment length and AADB, the direction of the relationship is not immediately apparent because two coefficients are involved with these variables. Figure 28 shows these relationships.

- Figure 29 depicts the relationships between AADB and bicycle crashes. Both relationships are increasing for most of the range of the two variables, except for the lower extreme of the two curves (i.e., segments shorter than 500 ft and AADBs approaching zero).



Source: FHWA.

Figure 28. Graph. Model San Francisco relationship between length and bicycle crashes.



Source: FHWA.

Figure 29. Graph. Model San Francisco relationships between AADB and bicycle crashes.

Next, the research team estimated CMFs defining appropriate contrasts involving the last three coefficients in table 44, as shown in table 45.

Table 45. Basic CMFs for bicycle crashes in San Francisco.

Condition	CMF	Estimate	Standard Error	*p*-Value	Significance
Flush buffer[a]	0.944	−0.0577	0.2664	0.8284	—
Vertical element[a]	0.509	−0.6758	0.3399	0.0468	*
Vertical element[b]	0.480	−0.7336	0.2417	0.0024	**
Vertical element[c]	0.494	−0.7047	0.2631	0.0074	**

—Not statistically significant.
*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
[a]Base condition: traditional bicycle lane.
[b]Base condition: flush buffered bicycle lane.
[c]Base condition: traditional or flush buffered bicycle lane.

All results in table 45 indicate statistically significant bicycle crash reductions for the presence of vertical elements as a separation of bicycle lanes from traffic. Compared to traditional bicycle lanes, SBLs are estimated to experience 49.1 percent fewer bicycle crashes (0.509 CMF statistically significant at the 0.05 significance level). Similarly, SBLs are estimated to experience 52.0 percent fewer bicycle crashes compared to bicycle lanes with flush buffers, (0.480 CMF statistically significant at the 0.01 significance level). When compared with locations with either traditional bicycle lanes or with flush buffers, this analysis also found that SBLs experience 50.6 percent fewer bicycle crashes (0.494 CMF statistically significant at the 0.01 significance level). Finally, although the analysis estimated bicycle lanes with flush buffers to perform better than traditional bicycle lanes, the estimate of that comparison was statistically insignificant (0.828 *p*-value for 0.944 CMF estimate).

Next, the research team proceeded to reestimate the model in table 44 to include differentiation between SBL types. Flexible posts and blended treatments were the two types of vertical element with enough representation in the San Francisco dataset to consider for CMF development. Accordingly, the refitted model included appropriate terms for these considerations. Table 46 shows the results of the model with these additions.

Table 46. Coefficient estimates for bicycle crash risk in San Francisco (*N* = 384 segments).

Parameter	Estimate	Standard Error	*t*-value	*Pr*(>|*t*|)	Significance
(Intercept)	3.306	2.6537	1.246	0.2137	—
Industrial land use	−0.655	0.3798	−1.725	0.0854	~
Mixed land use	1.831	0.5791	3.161	0.0017	**
Public land	−0.820	0.9087	−0.902	0.3675	—
Residential	0.952	0.6638	1.434	0.1525	—
Log(Length)	−1.194	0.4878	−2.447	0.0149	*
Length	0.002	0.0010	2.369	0.0183	*
One MV lane in each direction	0.457	0.2721	1.681	0.0937	~
Two MV lanes in each direction	−0.091	0.3043	−0.299	0.7655	—
No parking in one or both directions	−0.567	0.2865	−1.979	0.0486	*
Area bicycle = 1	0.155	0.1976	0.786	0.4324	—
Area bicycle = 2	1.135	0.3413	3.326	0.0010	***
Log(AADB+0.5)	−0.595	0.1787	−3.33	0.0010	***
AADB	0.012	0.0028	4.348	<0.0001	***
Traditional bicycle lane (both directions)	0.338	0.4318	0.782	0.4348	—
Buffered bicycle lane (both directions)	0.254	0.5102	0.497	0.6195	—
SBL (either direction)	0.536	0.9615	0.557	0.5776	—
Blended vertical elements (either direction)	−0.618	0.8132	−0.759	0.4482	—
Flexi-post vertical elements (either direction)	−1.325	0.8192	−1.618	0.1066	—

—Not statistically significant.
~Statistically significant at the 0.1 level.
*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
***Statistically significant at the 0.001 level.

Table 46 also shows that the addition of specific coefficients for the two types of vertical elements had a minimal effect on the rest of the coefficients in the initial model. Additionally, the two new coefficients clearly indicate reductions in bicycle crash risk (i.e., negative estimates), and safety performance seems to improve approximately twofold for flexible posts compared to blended vertical elements. Like the initial model, table 47 shows the corresponding CMF contrasts that can be constructed from the updated model.

Table 47. Detailed CMFs for bicycle crashes in San Francisco.

Condition	CMF	Estimate	Standard Error	*p*-Value	Significance
Flush buffer[a]	0.919	−0.0841	0.2675	0.7533	—
Flexible posts[a]	0.324	−1.1269	0.3519	0.0014	**
Flexible posts[b]	0.352	−1.0428	0.4141	0.0118	*
Flexible posts[c]	0.338	−1.0849	0.3602	0.0026	**
Blended[a]	0.658	−0.4192	0.2771	0.1304	—
Blended[b]	0.715	−0.3351	0.3732	0.3692	—
Blended[c]	0.686	−0.3772	0.3003	0.2091	—
Flexible posts[d]	0.493	−0.7077	0.3805	0.0629	~
Flexible posts or blended[a]	0.462	−0.7730	0.2532	0.0023	**
Flexible posts or blended[b]	0.502	−0.6890	0.3453	0.0460	*
Flexible posts or blended[c]	0.481	−0.7310	0.2716	0.0071	**

—Not statistically significant.
~Statistically significant at the 0.1 level.
*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
[a]Base condition: traditional bicycle lane.
[b]Base condition: flush buffered bicycle lane.
[c]Base condition: traditional or flush buffered bicycle lane.
[d]Base condition: blended vertical element.

As table 47 shows, the analysis determined that only some of the tested CMFs were statistically significant. The first and last three CMFs in table 47 should roughly correspond to the treatments and base conditions for the CMFs in table 45. Indeed, the corresponding estimates and standard errors in both tables are similar in magnitude. In addition to those comparable CMFs, the results in table 47 indicate statistically significant reductions in bicycle lane crash risks for flexi-post SBLs and either flexi-post or blended SBLs. For blended SBLs alone, the estimates suggest bicycle crash reductions, but those three CMFs were found to be statistically insignificant. Finally, table 47 also shows that the estimated CMF for flexi-post SBL versus blended SBL indicates a statistically significant reduction in bicycle crash risk (0.629 *p*-value for 0.493 CMF, statistically significant at the 0.10 level).

Cambridge Segment Analysis

Table 48 shows the observed conditions in the database, which includes 132 traditional bicycle lane sites, 23 buffered sites, and 24 vertical element sites (with buffer). Table 49 shows the results for the most parsimonious model of bicycle crash risk that does not include differentiation by type of SBL. In the case of Cambridge, the research team found no binomial overdispersion in the crash data, so they derived the estimates and standard errors from a maximum likelihood estimation model with binomially distributed response.

Table 48. Segments by bicycle lane condition per direction in Cambridge (*N* = 179).

Variable	Bicycle Lane (Direction 2)	Buffered (Direction 2)	Vertical Element (Direction 2)
Bicycle lane (direction 1)	132	0	0
Buffered (direction 1)	0	23	0
Vertical element (direction 1)	0	0	24

Table 49. Coefficient estimates for bicycle crashes in Cambridge (*N* = 179 segments).

Parameter	Estimate	Standard Error	*z*-Value	*Pr*(>|*t*|)	Significance
(Intercept)	−3.405	3.0172	−1.129	0.2591	—
Open space land use	−1.678	0.6973	−2.4060	0.0161	*
Log(AADT+05)	0.034	0.0341	1.0020	0.3165	—
Length	0.001	0.0004	2.2870	0.0222	*
Log(AADB+0.5)	−0.053	0.5653	−0.0940	0.9251	—
No parking in one or both directions	0.268	0.2184	1.2290	0.2191	—
Traditional bicycle lane (both directions)	−0.207	0.6279	−0.3300	0.7413	—
Buffered bicycle lane (both directions)	−0.814	0.8093	−1.0050	0.3147	—
SBL (either direction)	−1.035	0.9119	−1.1350	0.2564	—

—Not statistically significant.
*Statistically significant at the 0.05 level.

The results in table 49 differ from the results in San Francisco in various ways. In general, the Cambridge results indicate the following factors:

- Bicycle crashes significantly decrease at locations where the land use is open space, compared to other location types.
- The impact of AADB in bicycle crashes was found null in contrast with San Francisco, where crashes increased with increasing AADB.
- Bicycle crash risk increases with increasing segment length. The researchers found similar findings with the San Francisco model.

Next, the research team estimated CMFs defining appropriate contrasts from the Cambridge model, as shown in table 50.

Table 50. CMFs for bicycle crashes in Cambridge.

Condition	CMF	Estimate	Standard Error	*p*-Value	Significance
Flush buffer[a]	0.545	−0.6065	0.5022	0.2272	—
Vertical element[a]	0.437	−0.8276	0.7115	0.2447	—
Vertical element[b]	0.802	−0.2212	0.8606	0.7972	—
Vertical element[c]	0.592	−0.5244	0.7486	0.4836	—

—Not statistically significant.
[a]Base condition: traditional bicycle lane.
[b]Base condition: flush buffered bicycle lane.
[c]Base condition: traditional or flush buffered bicycle lane.

All results in table 50 indicate statistically insignificant bicycle crash reductions for conditions other than a traditional bicycle lane. This finding can be contrasted with the San Francisco results whereby CMFs indicated the presence of vertical element was statistically significant. The sample size for the Cambridge data is smaller, which could explain the lack of statistical significance. The results, however, are in the direction of, and with similar magnitudes to, the San Francisco CMFs.

The research team attempted fitting an expanded model, including differentiation by SBL type, similar to San Francisco; however, due to the smaller sample size for Cambridge and as shown when contrasting the relative size of the standard errors in table 45 and table 50, the variance of the estimates at least doubles for the Cambridge dataset. For that reason, the research team did not compute more specific CMFs for this dataset.

San Francisco and Cambridge Combined Segment Analysis

The researchers anticipated that the combined dataset between San Francisco and Cambridge was large enough to support a model with differentiation between SBL by vertical element type, so they directly developed a model that included San Francisco and Cambridge in addition to individual State models. Table 51 shows the coefficient estimates for the most parsimonious model of bicycle crash risk. The research team did not find binomial overdispersion in the combined dataset, so no adjustments were warranted for the estimates and standard errors in this case.

Table 51. Coefficient estimates for bicycle crash risk in San Francisco and Cambridge (N = 563 segments).

Parameter	Estimate	Standard Error	*z*-Value	*Pr*(>|*t*|)	Significance
(Intercept)	0.576	1.5527	0.370	0.7106	—
Industrial land use	−0.848	0.2650	−3.1990	0.0014	**
Mixed land use	0.956	0.2256	4.2370	<0.0001	***
Public land	−1.872	0.5807	−3.2230	0.0013	**
Residential	−0.021	0.2533	−0.0830	0.9342	—
Log(Length)	−0.669	0.2827	−2.3660	0.0180	*
Length	0.002	0.0006	2.5630	0.0104	*
One MV lane in each direction	0.469	0.1864	2.5160	0.0119	*

Parameter	Estimate	Standard Error	*z*-Value	*Pr*(>|*t*|)	Significance
Two MV lanes in each direction	0.119	0.2072	0.5730	0.5664	—
No parking in one or both directions	−0.264	0.1639	−1.6120	0.1069	—
Area bicycle = 1	0.148	0.1322	1.1210	0.2622	—
Area bicycle = 2	0.905	0.2497	3.6230	0.0003	***
Log(AADB+0.5)	−0.497	0.1412	−3.5180	0.0004	***
AADB	0.008	0.0015	5.5120	<0.0001	***
Traditional bicycle lane (both directions)	0.177	0.3227	0.5490	0.5832	—
Buffered bicycle lane (both directions)	−0.097	0.3797	−0.2540	0.7992	—
SBL (either direction)	−0.167	0.6628	−0.2520	0.8014	—
Blended vertical elements (either direction)	−0.119	0.5778	−0.2060	0.8366	—
Flexi-post vertical elements (either direction)	−0.944	0.5840	−1.6160	0.1061	—
City = San Francisco	0.891	0.1891	4.711	<0.0001	***

—Not statistically significant.
***Statistically significant at the 0.001 level.

The resulting coefficients are comparable to the ones obtained for San Francisco only. Additionally, when the site characteristics are comparable, this analysis found that the bicycle crash risk for San Francisco is roughly twice that for Cambridge (0.0004 *p*-value for a 0.668 estimate corresponding to an odds ratio of exp(0.668) = 1.950). Table 52 shows the estimated CMFs for various bicycle lane configurations derived from the model in table 51.

Table 52. CMFs for bicycle crashes in San Francisco and Cambridge.

Condition	CMF	Estimate	Standard Error	*p*-Value	Significance
Flush buffer[a]	0.761	−0.2737	0.2218	0.2172	—
Flexible posts[a]	0.276	−1.2875	0.3272	0.0001	***
Flexible posts[b]	0.363	−1.0139	0.3796	0.0076	**
Flexible posts[c]	0.316	−1.1507	0.3366	0.0006	***
Blended[a]	0.629	−0.4629	0.2760	0.0935	~
Blended[b]	0.828	−0.1893	0.3458	0.5842	—
Blended[c]	0.722	−0.3261	0.2925	0.2650	—
Flexible posts[d]	0.438	−0.8246	0.3808	0.0303	*
Flexible posts or blended[a]	0.417	−0.8752	0.2353	0.0002	***
Flexible posts or blended[b]	0.548	−0.6016	0.3092	0.0517	~
Flexible posts or blended[c]	0.478	−0.7384	0.2514	0.0033	**

—Not statistically significant.
[a]Base condition: traditional bicycle lane.
[b]Base condition: flush buffered bicycle lane.
[c]Base condition: traditional or flush buffered bicycle lane.
[d]Base condition: blended vertical element.
~Statistically significant at the 0.1 level.
*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
***Statistically significant at the 0.001 level.

The results are comparable to the results found in the San Francisco analysis albeit with a bigger combined sample size. This analysis found the CMFs for blended SBLs compared to traditional bicycle lanes was statistically significant, in addition to the same CMFs that were found significant in table 47.

Summary of SBL CMF Findings

The CMFs for SBLs show a clear trend in that with their implementation, a transportation agency can expect to see a reduction in bicycle crashes. The individual State models suffer from smaller sample sizes; however, they continue to result in estimated crash reductions consistent with those found with larger sample sizes. The combination of data from different States also results in similar trends and, for the most part, greater statistical significance. For the baseline conditions, the use of traditional bicycle lanes, bicycle lanes with buffers but no vertical elements, or bicycle lanes with a combination of traditional and buffers resulted in generally similar trends. The SBL treatments that were the most effective included flexi-post treatments and blended treatments (most often flexible posts and other vertical elements). Table 53 summarizes how the CMF values changed as the models were merged. This summary begins with San Francisco models only and then transitions to the merged model of San Francisco and Cambridge. The final merged State model included data from San Francisco, Cambridge, and Seattle. Generally, the resulting CMFs had a value of approximately 0.48. This value is a multiplicative factor that indicates a decrease in bicycle crashes of approximately 52 percent should be expected when bicycle lanes that are traditional or buffered are converted to SBL facilities.

This study included an analysis that focused on roadway segments. The research team assessed the prospect of using intersection-only and corridor-type models but found that for the available dataset, these two options did not yield statistically viable results.

Table 53. Summary of SBL CMF values for roadway segments.

Baseline Condition	Model CMF Treatment	San Francisco Only	San Francisco + Cambridge	San Francisco + Cambridge + Seattle	Suggested CMF
Traditional bicycle lane	Vertical element (varies)	0.509	—	—	0.51
Traditional bicycle lane	Flexible posts	0.324	0.276	0.498	0.28–0.50
Traditional bicycle lane	Flexible posts or blended	0.462	0.417	0.640	0.42–0.64
Flush buffered bicycle lane	Vertical element (varies)	0.480	—	—	0.48
Flush buffered bicycle lane	Flexible posts	0.352	0.363	0.441	0.35–0.44
Flush buffered bicycle lane	Flexible posts or blended	0.502	0.548	0.567	0.50–0.57
Traditional bicycle lane or flush buffered bicycle lane	Vertical element (varies)	0.494	—	—	0.49
Traditional bicycle lane or flush buffered bicycle lane	Flexible posts	0.338	0.316	0.468	0.32–0.47
Traditional bicycle lane or flush buffered bicycle lane	Flexible posts or blended	0.481	0.478	0.602	0.48–0.60

Seattle Segment Analysis

Table 54 shows the number of segments with bicycle lane characteristics per direction of travel.

Table 54. Number of segments by bicycle lane condition per direction in Seattle (*N* = 660).

Variable	Bicycle Lane (Direction 2)	Buffered (Direction 2)	Vertical Element (Direction 2)
Bicycle lane (direction 1)	484	4	10
Buffered (direction 1)	7	46	8
Vertical element (direction 1)	19	11	71

Table 55 shows the results for the most parsimonious model in Seattle of bicycle crash risk that does not include differentiation by SBL type. Similar to their findings with the Cambridge data, the research team found no binomial overdispersion in the Seattle crash data, so the model results reflect estimates and standard errors derived from a maximum likelihood estimation model with a binomially distributed response.

Table 55. Coefficient estimates for bicycle crash risk in Seattle (*N* = 660 segments).

Parameter	Estimate	Standard Error	*z*-Value	*Pr*(>|*t*|)	Significance
(Intercept)	−141.086	57.2177	−2.466	0.0137	*
Multi- or single-family land use	−1.0370	0.2186	−4.7440	<0.0001	***
Area bicycle = 1	1.0985	0.3247	3.3840	0.0007	***
Area bicycle = 2	0.1711	0.3493	0.4900	0.6242	—
log(ADT_1 + 0.5)	0.9394	0.2912	3.2270	0.0013	**
log(Length)	0.8965	0.1932	4.6410	<0.0001	***
log(AADB + 0.5)	26.1612	11.3722	2.3000	0.0214	*
AADB	−0.0799	0.0286	−2.7970	0.0052	**
Traditional bicycle lane (both directions)	−0.1207	0.4166	−0.2900	0.7719	—
Buffered bicycle lane (both directions)	−0.5266	0.4926	−1.0690	0.2850	—
SBL (both directions)	−0.4120	0.8554	−0.4820	0.6301	—

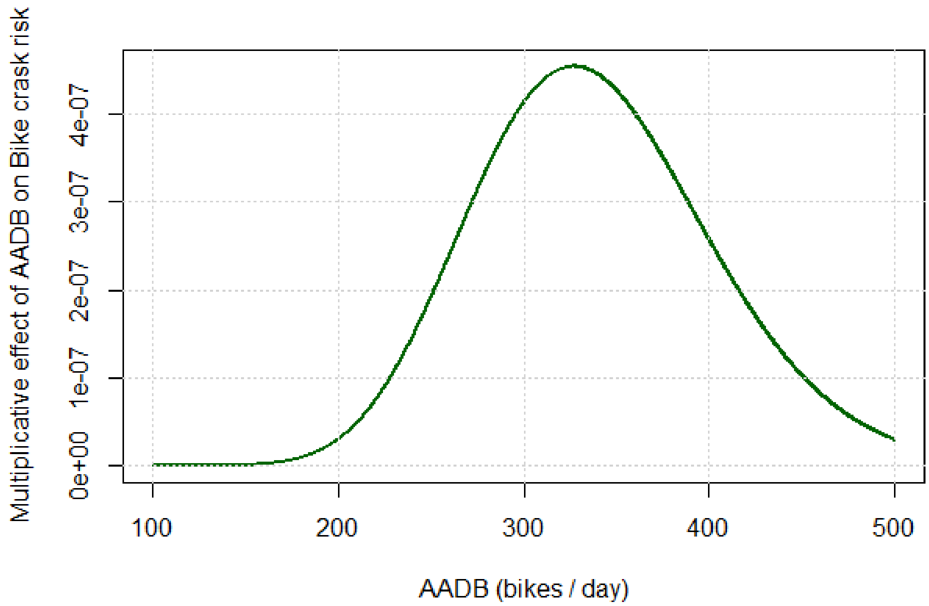
—Not statistically significant.
*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
***Statistically significant at the 0.001 level.
ADT_1 = Vehicles per day (exclusive only to the San Francisco traffic exposure).

The results in table 55 in general indicate the following factors:

- Bicycle crashes significantly decrease at locations where the land use is multi- or single family, compared to other land use types.
- Bicycle crash risk increases with increasing segment length, similar to the other two cities.

- Bicycle crash risk increases with increasing ADT_1.

The impact of AADB in bicycle crashes is strong, depending on the bicycle crash risk and AADB values. Figure 30 depicts the multiplicative effect of AADB on bicycle crash risk for Seattle.



Source: FHWA.

Figure 30. Graph. Seattle model relationships between AADB and bicycle crashes.

The model attributes a complex relationship with bicycle crash risk to AADB: Null from 100 to 200 bicycles/day, increasing from 200 to 330 bicycles/day, and decreasing from 330 to 500 bicycles/day. Next, the research team estimated CMFs defining appropriate contrasts from the Seattle model, as shown in table 56.

Table 56. CMFs for bicycle crashes (Seattle).

Condition	CMF	Estimate	Standard Error	*p*-Value	Significance
Flush buffer[a]	0.666	−0.406	0.354	0.251	—
Vertical element[a]	1.121	0.115	0.813	0.888	—
Vertical element[b]	0.747	−0.291	0.765	0.703	—
Vertical element[c]	0.915	−0.088	0.769	0.909	—

—Not statistically significant.
[a]Base condition: traditional bicycle lane.
[b]Base condition: flush buffered bicycle lane.
[c]Base condition: traditional or flush buffered bicycle lane.

All results in table 56 indicate statistically insignificant bicycle crash reductions compared to traditional bicycle lanes, similar to Cambridge and in contrast to San Francisco.

Next, the research team proceeded to reestimate the model shown in table 56, which includes differentiation between SBL types. Flexible posts and blended treatments were the two types of vertical elements with enough representation in the Seattle dataset to consider for CMF development. Accordingly, the refitted model included appropriate terms for these considerations. Table 57 shows the results of the model with these additions.

Table 57. Coefficient estimates for bicycle crash risk in Seattle (*N* = 660 segments).

Parameter	Estimate	Standard Error	*t*-value	*Pr*(>|*t*|)	Significance
(Intercept)	−136.820	61.309	−2.232	0.0256	*
Multi- or single-family land use	−1.039	0.222	−4.679	<0.0001	***
Area_bicycle=1	1.093	0.334	3.271	0.001	**
Area_bicycle=2	0.166	0.351	0.472	0.637	—
log(ADT_1+0.5)	0.928	0.296	3.139	0.002	**
log(Length)	0.895	0.193	4.627	<0.0001	***
log(AADB + 0.5)	25.333	12.180	2.080	0.038	*
AADB	−0.078	0.031	−2.514	0.012	*
Traditional bicycle lane (both directions)	−0.192	0.599	−0.321	0.748	—
Buffered bicycle lane (both directions)	−0.591	0.623	−0.948	0.343	—
SBL (both directions)	−0.351	0.945	−0.372	0.710	—
Blended vertical elements (either direction)	−0.274	1.476	−0.186	0.853	—
Flexi-post vertical elements (either direction)	−0.076	0.796	−0.095	0.924	—
No parking in one or both directions	−0.038	0.241	−0.156	0.876	—

—Not statistically significant.
*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
***Statistically significant at the 0.001 level.

The addition of specific coefficients for the two types of vertical elements had little impact on the rest of the coefficients in the initial model. The two new coefficients indicate reductions in bicycle crash risk (i.e., negative estimates), though these reductions are not statistically significant. Additionally, based on statistical analysis, the safety performance of flexible posts is slightly worse when compared to blended vertical elements. Table 58 shows the corresponding CMF contrasts that can be constructed from the updated model. This observation may be an artifact of the higher number of blended treatments than solitary SBL treatments.

All CMFs in table 58 are statistically insignificant. The following section uses a merged database using data from the three cities to produce updated CMFs.

Table 58. Reestimation of CMFs for bicycle crashes in Seattle.

Condition	CMF	Estimate	Standard Error	*p*-Value	Significance
Flush buffer[a]	0.671	−0.399	0.358	0.265	—
Flexible posts[a]	0.791	−0.235	0.836	0.779	—
Flexible posts[b]	1.178	0.164	0.883	0.853	—
Flexible posts[c]	0.965	−0.035	0.841	0.966	—
Blended[a]	0.649	−0.433	1.327	0.744	—
Blended[b]	0.966	−0.034	1.358	0.980	—
Blended[c]	0.792	−0.234	1.330	0.861	—
Flexible posts[d]	1.219	0.198	1.404	0.888	—
Flexible posts or blended[a]	0.716	−0.334	0.859	0.698	—
Flexible posts or blended[b]	1.067	0.065	0.905	0.943	—
Flexible posts or blended[c]	0.874	−0.134	0.864	0.876	—

—Not statistically significant.
[a]Base condition: traditional bicycle lane.
[b]Base condition: flush buffered bicycle lane.
[c]Base condition: traditional or flush buffered bicycle lane.
[d]Base condition: blended vertical element.

San Francisco, Seattle, and Cambridge Combined Segment Analysis

The researchers anticipated that the combined dataset between the three cities was large enough to support a model with differentiation between SBL by vertical element type, so they developed that model directly and did not depend on the models for the individual State. A visual inspection of the data in the combined dataset indicated that some fields were incomplete. In particular, several sites did not have an ADT value greater than zero. However, some of the AADB values were equal to zero because the bicycle exposure models use ADT as an input. Without additional information about the ADT, the team decided to remove all segments with either AADB or ADT having values of zero. Table 59 shows the coefficient estimates for the most parsimonious binomial model of bicycle crash risk using the combined data from the three cities.

Multiple factors were found to be statistically significant for bicycle crash risk, as table 59 shows. Additionally, after considering the impacts of other key variables, this analysis found remaining differences in bicycle crash risk for the three cities and in their relationship with AADB. In general, the analysis indicates the following factors:

- Bicycle crash risk is higher at locations with mixed land use.
- Bicycle crash risk is lower at locations with industrial or public land use.
- Bicycle crash risk is lower at locations with more MV lanes. The research team estimated that for each additional MV lane, bicycle crash risk decreases by a factor of 0.745 (0.745 = exp(–0.295)) when compared to roads with similar physical characteristic.

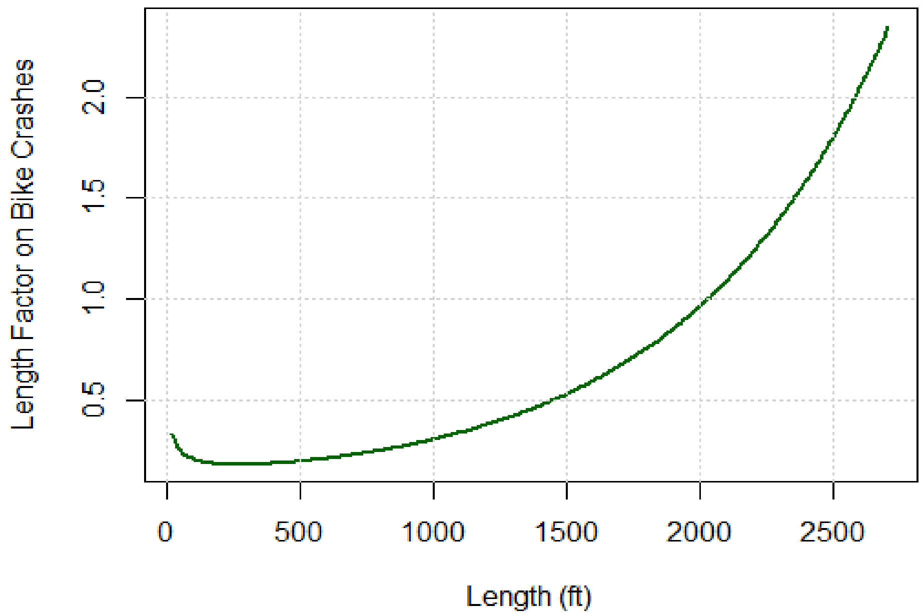
- Bicycle crash risk is lower at locations where parking is not permitted in at least one direction. The researchers estimated that bicycle crash risk at those locations is smaller by a factor of 0.718 (0.718 = exp(–0.331)), compared with locations without parking restrictions, other things unchanged.

Table 59. Coefficient estimates for bicycle crash risk in San Francisco, Seattle, and Cambridge (*N* = 1,223 segments).

Parameter	Estimate	Standard Error	*t*-value	*Pr*(>|*t*|)	Significance
(Intercept)	−2.826	3.0524	−0.926	0.3545	—
Mixed land use	0.985	0.1362	7.2340	<0.0001	***
Industrial land use	−0.708	0.2173	−3.2560	0.0011	**
Public land use	−1.826	0.5016	−3.6410	0.0003	***
log(Length)	−0.378	0.2274	−1.6640	0.0962	~
Length	0.001	0.0005	3.0320	0.0024	**
log(ADT_1 + 0.5)	0.093	0.0303	3.0570	0.0022	**
Area bicycle=1	0.271	0.1170	2.3160	0.0206	*
Area bicycle=2	0.655	0.1992	3.2890	0.0010	**
log(AADB + 0.5)	−0.028	0.5565	−0.0500	0.9602	—
log(AADB + 0.5):CitySEA	−6.958	1.0838	−6.4200	<0.0001	***
log(AADB + 0.5):CitySFO	−0.580	0.5449	−1.0640	0.2874	—
AADB	0.008	0.0012	6.6830	<0.0001	***
No parking in one or both directions	−0.331	0.1285	−2.5760	0.0100	*
Number of total MV lanes	−0.295	0.0602	−4.9000	<0.0001	***
CitySEA	40.215	6.2917	6.2917	<0.0001	***
CitySFO	3.692	2.8003	1.318	0.1874	—
Traditional bicycle lane (both directions)	−0.167	0.2866	−0.5840	0.5591	—
Buffered bicycle lane (both directions)	−0.047	0.3202	−0.1460	0.8841	—
SBL (either direction)	0.252	0.4879	0.5160	0.6058	—
Blended vertical elements (either direction)	−0.615	0.4227	−1.4550	0.1457	—
Flexi-post vertical elements (either direction)	−1.117	0.4241	−2.6340	0.0084	**

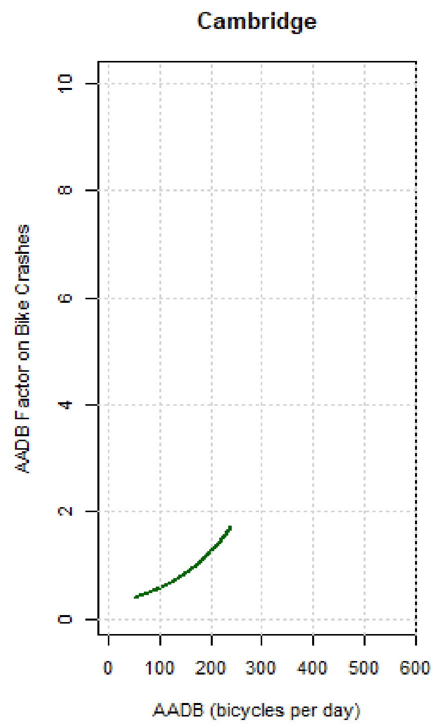
—Not statistically significant.
~Statistically significant at the 0.1 level.
*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
***Statistically significant at the 0.001 level.
CitySEA = City of Seattle; CitySFO = City of San Francisco.

The relationships between bicycle crash risk, segment length, and AADB were captured by multiple coefficients, so the trends are not immediately apparent. The plots in figure 31 and figure 32 demonstrate the trend lines for these two variables for Cambridge, whereas figure 33 and figure 34 represent the San Francisco and Seattle trends for AADB contrasted to bicycle crash risk.



Source: FHWA.

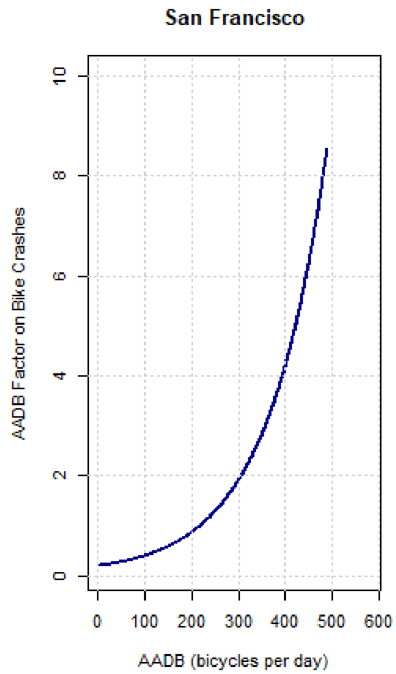
Figure 31. Graph. Model relationships and the influence of length on bicycle crashes for Cambridge.



Source: FHWA.

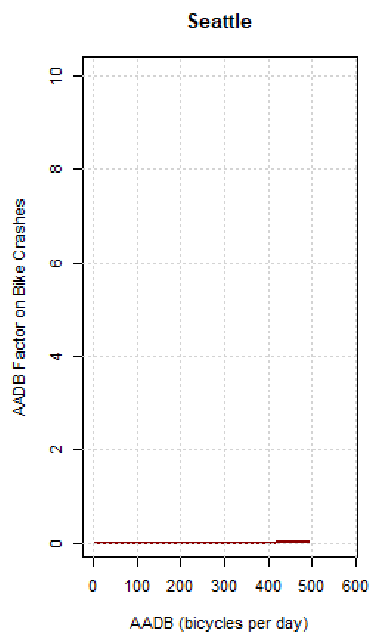
Figure 32. Graph. Model relationships between AADB and bicycle crashes for Cambridge.

The line on the graph for figure 33 shows that the relationship between AADB and bicycle crashes is exponential for San Francisco.



Source: FHWA.

Figure 33. Graph. Model relationships between AADB and bicycle crashes for San Francisco.



Source: FHWA.

Figure 34. Graph. Model relationships between AADB and bicycle crashes for Seattle.

In general, the bicycle crash risk increased with the increasing segment length, except for very short segments (lengths shorter than 100 ft), where the trend was reversed. Table 60 shows the estimated CMFs for various bicycle lane configurations derived from the model in table 59.

Table 60. CMFs for bicycle crashes in San Francisco, Seattle, and Cambridge.

Condition	CMF	Estimate	Standard Error	*p*-Value	Significance
Flush buffer[a]	1.128	0.121	0.173	0.484	—
Flexible posts[a]	0.498	−0.698	0.264	0.008	**
Flexible posts[b]	0.441	−0.819	0.297	0.006	**
Flexible posts[c]	0.468	−0.758	0.267	0.005	**
Blended[a]	0.822	−0.196	0.252	0.437	—
Blended[b]	0.729	−0.316	0.300	0.292	—
Blended[c]	0.774	−0.256	0.263	0.331	—
Flexible posts[d]	0.605	−0.502	0.318	0.114	—
Flexible posts or blended[a]	0.640	−0.447	0.203	0.028	*
Flexible posts or blended[b]	0.567	−0.568	0.253	0.025	*
Flexible posts or blended[c]	0.602	−0.507	0.212	0.017	*

—Not statistically significant.
*Statistically significant at the 0.05 level.
**Statistically significant at the 0.01 level.
aBase condition: traditional bicycle lane.
bBase condition: flush buffered bicycle lane.
cBase condition: traditional or flush buffered bicycle lane.
dBase condition: blended vertical element.

The results indicate that flexible posts separation is linked with a lower risk of bicycle crashes compared to the three base conditions without SBLs. Similarly, either flexible posts or blended separation is linked with a lower risk for bicycle crashes compared to the three base conditions without SBL. Although all the CMFs for blended separation imply bicycle crash reductions, none of these CMFs were statistically significant. The comparison between flexible posts and blended separation indicated better safety performance for flexible posts, although the statistical evidence behind this finding was weak (0.114 *p*-value for a 0.774 CMF estimate), indicating that although these analyses point in the direction that flexi-post could be a better option, both treatments might be similarly effective in reducing bicycle crash risk.

Validation Effort with Additional Data

As noted previously, the research team assessed the potential use of the two additional datasets (Austin and Denver) in this research. The research team used these additional data in combination with the multicity models developed earlier to assess the transferability of the analysis to other jurisdictions because the sample sizes were limited in these datasets, rendering full statistical analysis of each city impractical.

Analytical Approach

This section summarizes the research team's efforts to perform a statistical evaluation of the hypothesis that the multi-State model is transferable in general, and that the account for the bicycle vertical element is consistent with the data of each additional city.

Given the multicity model accounting for vehicle and bicycle exposure, geometry, land use, and presence of vertical elements, the product of the regression estimates and the set of variables of interest and their covariates define a linear predictor in the link scale. Then, for the new dataset, figure 35 provides an estimator of the linear predictor of the multicity model.

$$\widehat{\eta_{mc}} = X' \cdot \widehat{\beta_{mc}}$$

Figure 35. Equation. Estimator of the linear predictor.

Where:

β = the coefficient of the explanatory variable

X' = an individual observation

$\widehat{\eta_{mc}}$ = estimate of the linear predictor determined based on distributional parameters of scale (i.e., mean) and dispersion calculated using the original multicity model coefficient estimates.

If the data represent a behavior consistent with the multi-State analysis, this estimator should be such that, for the new dataset, the response variable for the new dataset is depicted as shown in figure 36.

$$Y \sim D\left(\widehat{\eta_{mc}}, \hat{\varphi}\right)$$

Figure 36. Equation. Response variable in new dataset.

Where:

Y = the response variable in the new dataset.

D = the corresponding conditional distribution of that variable.

$\left(\widehat{\eta_{mc}}, \hat{\varphi}\right)$ = the estimates of the distributional parameters of scale (i.e., mean) and dispersion calculated using the original multicity model coefficient estimates.

A test of this condition can be developed by relying on a regression estimation that allows additional multiplicative parameters in conjunction with the multicity model estimates under the hypothesis that the regression estimates values are statistically equal to 1.0 in the scale of the response—or equivalently, statistically equal to 0.0 in the link scale. In this case, this estimation would be the natural logarithm function.

To allow the estimation to better match the data at hand, the dispersion parameter can be allowed to be reestimated for each hypothesis test, given that the main interest is the linear predictor from the original multicity analysis (i.e., a hypothesis test only on the scale parameter). Therefore, the new model specification is such that figure 37 represents the linear predictor for the new dataset.

$$\hat{\eta} = \widehat{\eta_{mc}} + \gamma_0 + \gamma_1 \cdot X_{bl} + \gamma_2 \cdot X_{bb} + \gamma_3 \cdot X_{ve}$$

Figure 37. Equation. Linear predictor for the new combined dataset.

Where:

- $\hat{\eta}$ = the reestimated linear predictor on the new dataset.
- X_{bl} = the indicator variable for bicycle lane present.
- X_{bb} = the indicator variable for bicycle buffer present.
- X_{ve} = the indicator variable for vertical element present.
- Υ_0 = the overall correction for the overall correction for $\widehat{\eta_{mc}}$.
- Υ_1, Υ_2, *and* Υ_3 = the regression coefficients for corrections based on each of the three variables coding bicycle lane separation, X_{bl}, X_{bb}, and X_{ve}.

Although it might be interesting to draw conclusions from the individual regression estimates, this evaluation focused primarily on the specific linear contrast of Υ_1 and Υ_3 because that contrast represents the CMF estimate provided in the prior analysis.

Analysis and Results

For the exploratory analysis of the Austin data, the research team did not observe any concerning issues regarding the range and trends in the data, compared to the other cities. Table 61 shows descriptive statistics of the segments in the dataset. Table 62 summarizes the estimation of the validation parameters.

Table 61. Number of segments by bicycle lane condition per direction in Austin (*N* = 68).

Variable	Bicycle Lane (Direction 2)	Buffered (Direction 2)	Vertical Element (Direction 2)	Raised Lane (Direction 2)
Bicycle lane (direction 1)	13	1	0	0
Buffered (direction 1)	3	13	10	0
Vertical element (direction 1)	0	1	22	0
Raised lane (direction 1)	2	0	0	2
Landscaped buffer (direction 1)	0	1	0	0

Table 62. Estimates for validation analysis on Austin segments (*N* = 68).

Parameter	Estimate	Standard Error	*t*-value	*Pr*(>|*t*|)	Significance
Υ_0	1.276	2.35	0.543	0.589	—
Υ_1	2.286	2.695	0.848	0.4	—
Υ_2	−2.55	4.32	−0.59	0.557	—
Υ_3	2.738	2.414	1.134	0.261	—

—Not statistically significant.

Table 62 shows that all parameter estimates are statistically equivalent to 1.0. Therefore, the analysis fails to reject the null hypothesis, providing no statistical evidence of a different pattern in these data regarding the bicycle lane configuration variables compared to the multicity model.

For the Denver dataset, the research team observed very different trends than for other cities in the exploratory phase, namely, significantly higher counts of crashes in general and broader dispersion in the data. The researchers decided to focus on locations that had bicycle lanes only. Additionally, the team verified that only 13 locations had vertical elements on both directions, whereas 44 additional locations with the presence of vertical elements only had a single direction of travel. To still be able to leverage these additional data despite the significant differences, the research team modified the estimation to account for locations with traditional bicycle lanes, buffered lanes, or configurations with the buffer and vertical elements in either of the two directions of travel. Therefore, this assessment produced a new estimate for vertical element. Table 63 shows the descriptive statistics for the Denver dataset.

Table 63. Number of segments by bicycle lane condition per direction in Denver ($N = 384$).

Type of Bicycle Lane	Bicycle Lane (Direction 2)	Buffered (Direction 2)	Vertical Element (Direction 2)
Bicycle lane (direction 1)	231	4	2
Buffered (direction 1)	0	133	1
Vertical element (direction 1)	0	0	13

Next, table 64 shows the parameter estimates and standard errors for this analysis.

Table 64. Estimates for analysis on Denver segments ($N = 384$).

Parameter	Estimate	Standard Error	*t*-value	*Pr*(>|*t*|)	Significance
Υ_0	2.5972	1.414	1.837	0.067	~
Υ_1	−0.1118	1.4092	−0.079	0.937	—
Υ_2	−1.7785	1.4019	−1.269	0.205	—
Υ_3	−0.9674	1.5065	−0.642	0.521	—

Table 64 shows that except for the first coefficient, the estimation does not provide evidence of a deviation from the multicity model results.

Table 65 shows the contrast factor estimates for each of these analyses. The contrast factor is not statistically different from 1.0 in both cases.

Table 65. Hypothesis test result for vertical element CMF on Denver and Austin segments.

City	Condition	Contrast Factor	Estimate	Standard Error	*p*-Value	Significance
Austin	Vertical element	1.572	0.452	0.865	0.601	—
Denver	Vertical element	0.425	−0.856	0.880	0.331	—

—Not statistically significant.

The following two observations about these findings are relevant and merit consideration:

- Table 64 shows different specifications of bicycle lane variables for the case of Denver, which makes the comparison less direct in that case.

- The standard errors in both contrasts are comparable, indicating similarly low statistical power for the contrast for both datasets. The approximate range contrast factors that would produce similarly insignificant results for a standard error of that size is from 0.20 to 5.70. This range means that the validation effort would only be able to detect a significant difference in the contrast for contrast factors outside that range.

From this exercise, the research team concluded that regarding the safety of bicycle lane vertical separation elements, no significant differences existed between the multicity model and any of the two cities reviewed for the validation.

CHAPTER 8. CONCLUSIONS

The placement of effective design features, such as bicycle lanes, offers a safer and more efficient transportation system for all users. Therefore, the goal of this research effort was to determine whether constructing SBL facilities would provide additional safety opportunities by further reducing crashes beyond those reductions expected to occur along a corridor with basic design features, such as a traditional bicycle lane configuration.

SAFETY EFFECTS

To assess the safety effects of SBL facilities, the research team reviewed published SBL safety literature and found that the use of these facilities has largely occurred in European cities where SBL treatments have been applied largely to roads with differing functional purposes. As a result, this research explores the safety effects of SBL facilities in the United States.

Ideally, this assessment should have included known bicycle exposure volumes, just as ADT is typically incorporated in MV assessments. However, the implementation of SBLs in the United States is in its infancy, and multiyear bicycle counts are limited. In addition, the recent COVID-19 pandemic created challenges for research team members to travel to locations and conduct additional counts. Ultimately, the bicycle exposure variable, known as the AADB, was estimated based on a variety of bicycle count types that included short-term bicycle counts, periodic counts that occurred regularly (usually every 2 yr), and a few permanent bicycle count stations. The research team selected three of these cities for analysis and developed exposure estimates for the three cities (Cambridge; San Francisco; and Seattle). The analysis included sites with traditional bicycle lanes, buffered bicycle lanes, and SBLs. The analysis did not include shared-use paths or sharrow locations. After the SBL development, the team tested the equivalency of the resulting CMFs for two additional cities (Austin and Denver). The Austin findings were similar to those from the three study cities, but the Denver findings had some differences that could be attributable to seasonal or weather-related conditions.

RECOMMENDED CMFs

Ultimately, this research resulted in a series of statistically significant CMF values. The use of a CMF requires knowledge of the before treatment (e.g., a traditional bicycle lane) and the after treatment (e.g., an SBL). The team found no statistically significant influence on safety for sites with a CMF equal to 1.0. A CMF greater than 1.0 indicates that more crashes can be expected, whereas a CMF value less than 1.0 indicates a reduction in crashes. Based on the findings depicted in table 60, the CMF values shown in table 66 can be used when assessing the potential safety influence of adding an SBL to an existing facility. Clearly, these findings indicate that the implementation of SBL facilities will help reduce crashes. In addition, a more consistent application of flexible posts will provide an additional measure of safety compared to a blend of vertical elements along a corridor.

Table 66. CMFs for converting to an SBL.

Significance Level	Before Condition	After Condition	CMF	Standard Error
0.01	Traditional bicycle lane	SBL with flexible posts	0.498	0.173
0.01	Flush buffered bicycle lane	SBL with flexible posts	0.441	0.297
0.01	Traditional or flush buffered bicycle lane	SBL with flexible posts	0.468	0.267
0.05	Traditional bicycle lane	SBL with blend of flexible posts and other vertical elements	0.640	0.203
0.05	Flush buffered bicycle lane	SBL with blend of flexible posts and other vertical elements	0.567	0.253
0.05	Traditional or flush buffered bicycle lane	SBL with blend of flexible posts and other vertical elements	0.602	0.212

FUTURE RESEARCH

The research team encountered two significant challenges for this effort. First, the limited access to bicycle count data and the impact of the historic pandemic with a typical bicycle usage rendered acquiring comprehensive bicycle count information infeasible. Fortunately, this bicycle issue is a challenge that should resolve itself over time. Currently, several initiatives are underway to bolster bicycle count information for many cities and States. Consequently, as the SBL facilities continue to be implemented and the bicycle exposure data collection improves, the development of consistent and reliable bicycle exposure numbers can be expected to improve.

The second challenge is the inconsistent nature of SBL applications, particularly at approaches to intersections. Initially, the research team hoped to develop CMFs for segments and intersections, but their attempts to model intersections and/or entire corridors were unsuccessful. Consequently, the team focused on developing robust CMFs for segments. Future work may be to conduct research that estimates the safety effect of the various types of SBL-to-intersection transitions.

This report does demonstrate that as bicycle facilities continue to evolve in the United States, a better understanding of how expanded configuration types will influence crashes will be needed. However, the team did determine from this research that SBLs do provide a clear safety benefit and reduce crashes by as much as 50 percent or more at segment locations.

ACKNOWLEDGMENTS

The maps in figure 2 through figure 4 were modified by the authors of this report. The original maps are the copyright property of Google® Earth™ and can be accessed from https://www.google.com/earth.[24] Figure 2 was modified by the addition of a red dot to indicate the location at Anderson Bridge, JFK Street, and Memorial Drive in the City of Cambridge. In figure 3, arrows were added to show the movements of the bicyclists at the intersection. In figure 4, dots were added to show data points indicating bicyclists.

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