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SYSTEMIC ANALYSIS OF BICYCLE AND PEDESTRIAN SAFETY IN UTAH

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RESEARCH
UDOT Keeping Utah Moving
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4501 South 2700 West - P.O. Box 148410 - SLC,UT 84114-8410

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16. Abstract

The objective of this systemic analysis of bicycle and pedestrian safety in Utah was to identify risk factors, potential treatment sites, and potential countermeasures. The systemic approach to roadway safety management is a proactive means of identifying risk factors, countermeasures, and (high-risk, rather than just high-crash) treatment locations. First, a literature review identified practices for systemic safety analysis and risk factors for bicycle/pedestrian crashes from previous research. Second, the data collection process selected study locations (segments, signalized, and non-signalized intersections), assigned pedestrian/bicycle-involved crashes (2010–2019) to those locations, and assembled data on exposure, transportation (roadway geometry and traffic), and neighborhood community (land use, built environment, and sociodemographic) characteristics. Third, data analysis generated results from 48 Poisson or negative binomial crash frequency models, segmented by: mode, location type, crash type (all or fatal and serious injury), network type (state only or state and federal aid), and with or without exposure. Altogether, these efforts generated risk factors for bicycle and pedestrian crashes at various types of locations. Fourth, potential countermeasures (linked to specific risk factors) were listed. Fifth, an example interactive interface—displaying model results and empirical Bayes estimates of crash frequencies—was developed to help identify potential treatment locations using filtering and/or ranking. Finally, recommendations for implementation focused on mitigating data limitations through improved/expanded data collection processes, integrating the results and interface into existing safety management tools and processes, and repeating this systemic analysis periodically to continue improving safety outcomes for people walking and bicycling in Utah.

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UNIT CONVERSION FACTORS

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 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 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 (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. (Adapted from FHWA report template, Revised March 2003)

LIST OF ACRONYMS

AADB	Annual Average Daily Bicyclists
AADP	Annual Average Daily Pedestrians
AADT	Annual Average Daily Traffic
AASHTO	American Association of State Highway and Transportation Officials
ACS	American Community Survey
ATSPM	Automated Traffic Signal Performance Measures
CMF	Crash Modification Factor
DDI	Diverging Diamond Interchange
DLT	Displaced Left Turn
DOT	Department of Transportation
DPS	Department of Public Safety
EB	Empirical Bayes
FA	Federal Aid
FHWA	Federal Highway Administration
GIS	Geographic Information Systems
GPS	Global Positioning System
HAWK	High-Intensity Activated Crosswalk
HSM	Highway Safety Manual
HSO	Highway Safety Office
HSRC	Highway Safety Research Center
LEHD	Longitudinal Employer Household Dynamics
LBI	Leading Bicycle Interval
LBS	Location-Based Services
LPI	Leading Pedestrian Interval
ML	Machine Learning
MPO	Metropolitan Planning Organization
NACTO	National Association of City Transportation Officials
NB	Negative Binomial
NCHRP	National Cooperative Highway Research Program
PHB	Pedestrian Hybrid Beacon

RTM	Regression to the Mean
RTOR	Right Turn on Red
SLD	Smart Location Database
SPF	Safety Performance Function
SPUI	Single Point Urban Interchange
SR	State Route
TWLTL	Two-Way Left-Turn Lane
UDOT	Utah Department of Transportation
UGRC	Utah Geospatial Resource Center
UNC	University of North Carolina
US	United States
WFRC	Wasatch Front Regional Council

EXECUTIVE SUMMARY

The objective of this systemic analysis of bicycle and pedestrian safety in Utah was to identify risk factors, potential treatment sites, and potential countermeasures, with an ultimate goal to help improve safety outcomes for people walking and bicycling on Utah roadways. Compared to a traditional site-based hot-spot safety analysis, the systemic approach is a proactive means of dealing with the limitations of the highly dispersed nature of pedestrian and bicycle crashes (many sites with only a few crashes). Specifically, the systemic approach utilizes past research and empirically-derived relationships between crashes and various (roadway, transportation, and contextual) characteristics to identify risk factors, which are later used to determine potential countermeasures and high-risk (rather than high-crash) treatment locations.

To accomplish the research objective, this project undertook several major tasks. First, a review of the literature identified best practices for systemic safety analysis, methods for risk factor identification, and (most importantly) risk factors for pedestrian and bicycle crashes as found in previous research. Second, a large-scale data collection process first selected study locations across Utah (segments or mid-block locations, signalized intersections, and non-signalized intersections), assigned crashes (pedestrian- or bicycle-involved, from 2010 through 2019) to those locations, and assembled a variety of data on exposure, transportation (roadway geometry and traffic) characteristics, and neighborhood community (land use, built environment, and sociodemographic) characteristics from various sources. Third, a robust data analysis process generated results from 48 Poisson or negative binomial regression models of crash frequencies, segmented by: mode (pedestrian or bicycle), location type (segments, non-signalized or signalized intersections), crash type (all or fatal and serious injury), network type (state-only or state and federal aid roads), and variable specification (with or without exposure).

Altogether, these efforts generated a lengthy tabulation of risk factors for bicycle and pedestrian crashes at various types of locations, based on a combination of information from the literature review and the crash frequency models. Fourth, a list of potential countermeasures (from published research reports and guidebooks) was developed, with countermeasures linked to specific risk factors. Fifth, an example interactive interface and web app was developed to aid in the filtering and/or ranking process of identifying potential treatment sites, and to generate lists of the top-10 potential treatment sites (by mode and location type) based on anticipated pedestrian/bicycle crashes.

To improve bicycle and pedestrian safety in Utah, the key findings and recommendations need to be implemented, requiring sustained efforts over several years from various stakeholders and in multiple areas. The implementation plan makes several recommendations. The most important step is to implement the findings and interface into existing tools and procedures, such as bicycle/pedestrian safety performance functions and countermeasures, enhancements to the Numetric safety analysis system, and subsequent functionality refinements. Other recommendations include improving bicycle/pedestrian data (on facilities, exposure, and crashes) and roadway/intersection data (for consistency, to locate intersections with attributes, to cover local roads, and historical archiving) to mitigate some of the limitations and data challenges encountered as part of this project. The final recommendation is to repeat this systemic analysis periodically, in order to continue improving safety outcomes for people walking and bicycling in Utah.

1.0 INTRODUCTION

1.1 Problem Statement

The number and share of pedestrian and bicyclist injuries and fatalities has been increasing, both in the US and in Utah. According to the National Highway Traffic Safety Administration, there were more than 6,800 pedestrian and bicyclist deaths in traffic crashes in 2016, representing over 18% of all traffic fatalities (NHTSA, 2018a, 2018b). This was a substantial increase since 2007, when there were only 5,400 deaths (13%). Although Utah has seen decreases in bicyclist crashes and injuries in recent years, pedestrian crashes and injuries have increased. In 2016, 44 deaths (representing nearly 17% of all fatal crashes) and more than 1,500 injuries to people walking and bicycling on Utah streets and highways were reported (Utah DPS, 2017). Through the month of April, 2022 is on pace for the most fatal pedestrian crashes on record in Utah (Boal, 2022). These statistics highlight the need to focus on pedestrian and bicyclist safety.

Transportation agencies can approach the roadway safety management process in two general ways. Traditionally, a crash-based approach selects sites (through network screening) and identifies site-specific safety issues (through diagnosis) using historical data on reported crashes and local conditions at sites, informing the selection of site-specific safety countermeasures and treatments. While useful, this crash-based approach has limitations for addressing bicycle and pedestrian safety concerns. Crashes involving people walking and bicycling are (compared to motor vehicle crashes) highly dispersed, with many sites that have only a few crashes. Such highly dispersed crashes are difficult to address using site-based crash histories. Similarly, such site-based methods may not be able to address specific crash types (like bicycle & pedestrian crashes) due to their low frequencies. Finally, many performance measures used in the crash-based approach require exposure data, which remain difficult to obtain for walking and bicycling.

An alternative and often complementary approach, the systemic approach, may be better suited for tackling many bicycle and pedestrian safety issues in a state like Utah. Rather than relying upon reported crashes to select and apply treatments to high-crash sites, a systemic approach to safety management instead first selects crash type(s) of interest and identifies geometric and operational risk factors across a network that are associated with those crash type(s), using crash data from a variety of sites and prior knowledge. Then, these risk factors guide the selection of sites with higher-risk characteristics, informed by, but without having to rely upon, site-specific crash histories or requiring exposure data. Systemic safety analysis is proactive, identifying potential improvements without waiting for crash histories and trends to develop. Systemic safety programs often recommend lower-cost proven countermeasures that can be applied to a larger number of sites, potentially increasing returns on investment. A recent National Cooperative Highway Research Program (NCHRP) Report 893, "Systemic Pedestrian Safety Analysis" (Thomas et al., 2018), demonstrates how to apply the systemic approach to pedestrian safety analysis.

Given the highly dispersed nature of bicycle and pedestrian crashes and the relative lack of exposure data for these modes, the systemic approach is a promising way to meet the need to address bicycle and pedestrian safety issues throughout the state of Utah. This research applies the data-driven systemic approaches described in NCHRP Report 893 to address both pedestrian and bicyclist safety on Utah roadways.

1.2 Objectives

The primary objective of this research project is to conduct a systemic analysis of bicycle and pedestrian safety in Utah, in order to identify risk factors, potential treatment sites, and potential countermeasures.

1.3 Scope

This project accomplishes this research objective through the following major tasks:

1. Define the scope of the systemic safety analysis, including target crash types and specific roadway networks or study areas.
2. Conduct a literature review of systemic bicycle and pedestrian safety analyses. Review academic research, government reports, and case studies to determine innovative and best practices in systemic safety analysis for walking and bicycling.

3. Compile necessary and available data for the systemic analysis. Data include:
    a. Bicycle and pedestrian crashes (frequencies, types, contributing factors, and locations) from existing UDOT and Utah crash databases;
    b. Any available measures of bicycle and pedestrian exposure (such as Strava data, permanent nonmotorized counters, and pedestrian push-button data at traffic signals);
    c. Geometric and operational characteristics of selected roadway facilities (speeds, # lanes, shoulders, bike lanes, sidewalks, access points, horizontal/vertical curves, pavement conditions, crossing treatments, traffic control devices, etc.) and/or characteristics of the surrounding community (sociodemographics, land uses, etc.) from existing UDOT and Utah GIS databases.
4. Determine risk factors for bicycle and pedestrian crashes. Risk factor determination involves the development of safety performance functions (SPFs) predicting bicycle and pedestrian crash frequencies as a function of potential risk factors identified in Task 3, while also incorporating prior research and expert knowledge.
5. Identify potential treatment sites with high risk for bicycle and pedestrian crashes. NCHRP Report 893 lists several site selection approaches that can be utilized, including: filtering and sorting based on risk factor presence, ranking based on estimated crashes, or a combination of the two.
6. Recommend potential systemic countermeasures to apply at the treatment sites. Countermeasures should be related to the target crash types and roadway facilities, have a documented safety effectiveness, and be cost-effective and feasible to implement across a number of potential treatment sites in the study network. Resources for countermeasure selection include FHWA's Crash Modification Factor Clearinghouse and the PEDSAFE and BIKESAFE Guides and Countermeasure Selection Systems, among others.
7. Prepare an interactive web map highlighting potential treatment sites and countermeasures to improve bicycle and pedestrian safety in Utah.

1.4 Outline of Report

This report is organized into the following chapters:

- Chapter 1.0 contains an introduction to the research, including the problem statement, study objectives, scope and tasks, and the organization of the report.
- Chapter 2.0 includes a literature review of risk factors for bicycle and pedestrian crashes, as well as a review and summary of systemic safety analysis.
- Chapter 3.0 details the scope of the analysis, including target crash types and specific roadway networks and study locations, as well as the data collection and assembly process, including crash data, exposure data, geometric and operational data, and data on the surrounding community.
- Chapter 4.0 reports the results of count data regression models analyzing pedestrian and bicycle crash frequencies (for different modes, severity levels, facility types, and data availability), including summarizing results from and comparisons between different models regarding goodness of fit and factors associated with pedestrian and bicycle crashes.
- Chapter 5.0 applies the models of pedestrian and bicycle crash frequencies towards a systemic analysis of bicycle and pedestrian safety, including the determination of risk factors and potential countermeasures, and the identification of potential treatment sites and countermeasures.
- Chapter 6.0 summarizes the report by highlighting the major findings, comparing those findings with earlier research, and noting study limitations.
- Chapter 7.0 provides recommendations for implementation of the research findings, including recommended potential systemic countermeasures to apply at the potential treatment sites.

2.0 RESEARCH METHODS

2.1 Overview

In order to develop risk-based systemic safety models for pedestrian and bicycle crashes, it is important to understand from the literature both the process of systemic safety analysis as well as the factors that increase the risk level for these types of crashes. This chapter begins by reviewing the recommended practices as well as case study examples of systemic safety analysis. Next, different methods for identifying risk factors from quantitative crash data are summarized. Finally, the largest sections of the chapter review the literature on possible risk factors for first pedestrian and then bicycle crashes, including various roadway, intersection, traffic, built environment, and other characteristics.

2.2 Systemic Safety Analysis

Since 2010, there has been an increase in the number of automobile crashes involving pedestrians and cyclists in Utah. Other states have been facing a similar problem and have attempted to address the issue, in part, with a systemic approach to bicycle and pedestrian safety analysis. To help understand the application of a systemic approach to safety analysis in Utah, a study of industry-recommended practices and several case studies is conducted. This section identifies the common and best practices used today, notes potential limitations, and discusses ways to overcome these restrictions.

The systemic safety analysis study methods come from various articles examined here in two groups: recommended practices and case studies. Recommended practices are derived from four reports published in recent years by the Federal Highway Administration (FHWA) or the National Cooperative Highway Research Program (NCHRP). Case studies come from a number of different projects across the United States, comprising a variety of project scales, goals, and outcomes. Once the study methods are outlined, similarities and differences are discussed. Existing limitations faced by the case studies are then detailed and possible innovations for Utah are provided.

2.2.1 Systemic Safety Analysis Study Methods

The methods used in a systemic safety analysis study follow a basic outline. The scope of the project is defined, data are compiled and analyzed, and treatment locations and countermeasures are selected. Following some refining, the project is implemented and then evaluated according to the impacts made. For an example of this process, see Figure 2.1. In this section, we first describe the recommended practices for systemic safety analysis study methods and then document case studies that applied these methods.

2.2.1.1 Recommended Practices

The current recommended practices for systemic safety analysis in the US can be summarized from four national publications. Specific to pedestrian safety (but depicting a generally applicable process) is the NCHRP Research Report 893, "Systemic Pedestrian Safety Analysis" (Thomas et al., 2018). This document gives seven steps to completing a systemic safety analysis. The first step is to define the scope of the study by designating the project's geographic area, facility or location type of interest, and the crash types to inspect. Step two involves compiling the necessary data on the target roadways and related crash information. Next, risk factors for the selected locations are determined through data analysis. Locations in need of treatment due to these risk factors are then identified in step four. Step five involves selecting appropriate countermeasures that may be used at the identified treatment sites to reduce risks. Following further refinement of the project, the treatment plan is implemented. Finally, the effectiveness of the project is evaluated before starting the process over. See Figure 2.1 for an outline of this process.

Figure 2.1 Systemic Safety Analysis Process (Thomas et al., 2018)

The second document is an FHWA publication, "Guide for Scalable Risk Assessment Methods for Pedestrians and Bicyclists," by Turneret al. (2018). This report gives eight steps to completing a scalable risk assessment, which together fit well within the first three steps of the Thomaset al. (2018) systemic pedestrian safety analysis process. To start, the uses of risk values, such as safety performance measures or countermeasure evaluation, are determined. Next, a geographic scale is selected. Specific risk definitions are then made to help calculate quantitative risk values (such as crash rates or expected crashes). A choice is then made regarding the measure of exposure, whether that is by distance or time traveled, traffic volume or counts, trips made, or an area's population. Step five involves selecting an analytic method to estimate exposure in the area defined earlier. With this choice made, the analytic method is then employed to estimate the exposure measure. Next, other data are compiled as based on the risk definitions from step three. Finally, risk values are calculated using the output from steps six and seven.

The third article examined is the “Reliability of Safety Management Methods: Systemic Safety Programs” report by Gross et al. (2016) and published by FHWA. Section 2 of this document contains information on a systemic approach to road safety management. Three main steps are given as identifying the focus crash, facility, or risk types; screening and prioritizing candidate locations; and selecting appropriate countermeasures. Again, this matches well with steps one through five from Thomaset al. (2018). Two variations on the systemic approach are also discussed; both modify the information or methods used to identify treatment locations and/or select countermeasures. The first is the “Benefit-Cost Threshold” variation in which benefit-cost ratio thresholds (e.g., based on minimum crash rates) are used to prioritize treatment sites identified from the systemic analysis, thus achieving a higher return on investment. The second is the “Hybrid Systemic and Crash-Based” variation, which starts by identifying the focus crash type as in the systemic approach, but then screens sites using performance measures as in a crash-history-based analysis.

The fourth resource is the FHWA publication, “Systemic Safety Project Selection Tool,” by Preston et al. (2013), and it suggests steps similar to the other articles. First, focus crash types and risk factors are identified. Then, candidate locations are screened and prioritized. Appropriate countermeasures for the crash types and risk factors are selected, and then projects are prioritized and carried out. Additionally, an evaluation of the systemic safety program is conducted, and the process begins again.

A brief summary of these articles about recommended practices for systemic safety analysis is found in Table 2.1. For each document, this table shows the requirements to define the scope, data collection needs, the process for using the data to determine risk factors or identify potential treatment locations, and possible outcomes of this process.

Table 2.1 Comparison of Systemic Safety Analysis Recommended Practices

Document	*Scope*	*Data*	*Process*	*Outcomes*
Systemic Pedestrian Safety Analysis (Thomas et al., 2018)	• Area or network • Facility type • Crash type	• Crashes • Exposure • Roadway, intersection	• Safety performance functions • Crash frequencies • Research, judgment	• Treatment sites • Countermeasures • Treatment plan
Guide for Scalable Risk Assessment Methods for Pedestrians and Bicyclists (Turner et al., 2018)	• Purpose of risk assessment • Geographic scale • Risk definition	• Crashes • Exposure • Other risk indicators	• Exposure estimation • Risk value calculation	• Risk values
Reliability of Safety Management Methods: Systemic Safety Programs (Gross et al., 2016)	• Facility type • Crash type	• Crashes • Risk factors	• Benefit-cost threshold • Hybrid systemic and crash based	• Screened and prioritized locations • Countermeasures
Systemic Safety Project Selection Tool (Preston et al., 2013)	• Facility type • Crash type	• Crashes • Exposure • Roadway, intersection	• Research • Statistics • Crash modification factors	• Screened and prioritized locations • Countermeasures

2.2.1.2 Case Studies

Eight case studies of systemic safety analysis for active transportation (pedestrian and bicycle) safety were reviewed, each with a different project scope and outcome. Four were contained in the “Systemic Pedestrian Safety Analysis” NCHRP report; see Thomas et al. (2018) for more detailed information. The key findings from these case studies are summarized below.

In the first case study (Thomas et al., 2018), the Seattle DOT focused their scope on pedestrian crashes at intersections within the City of Seattle, WA, as well as a narrower scope of crashes involving crossing pedestrians struck by a through-moving motor vehicle. Requisite data about crashes and roadways were compiled from regional databases, and exposure data (pedestrian volumes) were estimated using built-environment characteristics like population density. Negative binomial regression modeling was used to develop safety performance functions (SPFs) and identify risk factors. The results—a combination of SPF model-predicted crashes and prior observed crashes using an empirical Bayes method—were used to create a GIS-based tool to rank intersections and screen locations for potential treatment. As noted in the report, “City staff also mentioned that while the initial data compilation was time-consuming, the cost was not that high, and the resulting knowledge and tools were well worth the investment” (p. 61).

The second case study (Thomas et al., 2018) involves the Oregon DOT’s work on a statewide bicycle and pedestrian safety plan. Due to a lack of consistent roadway data for local roads, the scope was restricted to state highways only. Rather than using a model, bicycle and pedestrian crash risk factors were identified and weighted using an expert panel. A spatial analysis model then prioritized 0.10-mile segments using crash history and risk factor scores, and combined segments into corridors. With the analysis complete, a list of potential countermeasures was developed to help in developing and refining the treatment plan for identified corridors.

In the third case study (Thomas et al., 2018), the Arizona DOT implemented a systemic program for their pedestrian safety action plan. The scope included segments and intersections on state highways. Rather than rely on prior crash histories (like the Oregon DOT), they also assembled data from existing spatial databases, weighted risk factors identified from the pedestrian safety literature, and used a GIS-based risk-scoring tool to identify potential treatment locations with likely pedestrian activity. In selecting potential countermeasures and refining a treatment plan, the DOT applied benefit-cost analysis to help with the prioritization process.

The fourth case study (Thomas et al., 2018) documents the California DOT’s (Caltrans’) quasi-systemic approach to supplement their traditional hot-spot analysis for the pedestrian safety program. The scope focused on urban arterials, and risk factors were pre-identified from previous research. Thus, data included both crash frequencies by location type and roadway data on facility types related to risk factors. A “systemic hot-spot” matrix identified the kinds of locations and crash types with high crash frequencies, and then appropriate potential countermeasures were considered for each location and crash type.

Another (fifth) case study based in Seattle, Washington, is documented in the article by Kumfer et al. (2018). The study's scope had a specific focus on two types of midblock/segment pedestrian crashes: those between pedestrians and motor vehicles traveling straight, and pedestrian crashes with motor vehicles under dark conditions. Using eight years of crash data, estimates of pedestrian volumes, as well as roadway and other locational information from existing databases, the authors developed two SPFs using negative binomial regression. An earlier novel step used machine learning methods (conditional random forest regression) to identify potentially statistically significant risk factors. City of Seattle staff then used a GIS tool that included various measures of risk—SPF-predicted crashes, empirical Bayes weighted estimates, etc.—in their screening and ranking process.

The sixth case study involves research investigating pedestrian and bicycle crash risk and equity by Lindsey et al. (2019). This study used data in Minneapolis, Minnesota, from 2005 to 2017, and the scope included crashes involving a pedestrian or bicyclist at intersections and mid-block street segments. GIS was used to categorize crashes as having occurred at an intersection or mid-block, and vehicular, pedestrian, and bicycle counts were used for exposure. Other correlates of crash risk—including roadway and intersection characteristics—were also assembled. Negative binomial regression was used for analysis of the collected data. The researchers suggested that the City of Minnesota could use the findings (predicted crashes) for ranking and scoring locations and thus prioritizing improvement projects to improve safety while considering equity.

The seventh case study is research on risk factors for pedestrian and bicycle crashes by Monsere et al. (2017). Working with the Oregon DOT, this project randomly selected 188 segments and 184 intersections on urban arterials throughout the state of Oregon. Bicycle and pedestrian crash data at these segments and intersections from 2009 to 2013 were collected, along with segment and intersection characteristics. By obtaining cyclist exposure data from Strava, the bicycle models were significantly improved. Analysis was completed using logistic regression (site experienced a crash or not) where significant variables were selected using a combined backward and forward stepwise method, along with important variables identified by appropriate literature. From the results, a risk-scoring tool based on the presence of risk factors was developed and then applied to Oregon DOT projects.

The final (eighth) case study involved a systemic safety analysis focused on bicycle and pedestrian safety in Iowa (Iowa DOT, 2020). This study used ten years of pedestrian and bicycle crash data from 2009 through 2018, and separated locations into urban and rural segments and intersections. Within each location type, segment and intersection attributes were obtained and categorized, and crash rates were calculated for each attribute level. The rates were converted into a normalized score for each attribute, and then the attributes were weighted to form a composite score. Composite scores were then calculated for all segments and intersections, allowing locations to be ranked by their scores, and a GIS mapping tool displayed the results.

A brief summary of these articles is found in Table 2.2. This table shows how each case study met the requirements for scope and data, processed the data, and any outcomes or products.

Table 2.2 Comparisons of Scope, Data, Process, and Outcome by Systemic Case Study

Document	*Scope*	*Data*	*Processes*	*Outcomes*
Case Example 1 (Thomas et al., 2018)	Intersections, Seattle, Washington	Crashes, intersection	SPF, empirical Bayes	GIS-based tool for screening and ranking intersections
Case Example 2 (Thomas et al., 2018)	State highway segments, Oregon	Crashes, roadway	Crash history, expert-weighted risk factors	Corridors, segments, countermeasures, treatment plan
Case Example 3 (Thomas et al., 2018)	State highway segments and intersections, Arizona	Roadway, intersection	Weighted risk factors from literature	GIS tool, sites, countermeasures, treatment plan
Case Example 4 (Thomas et al., 2018)	Urban arterials, California	Crashes, roadway	Matrix of crash type and location type	Countermeasures for crash/location-type matrix cells
Midblock Pedestrian Crash Predictions in a Systemic, Risk-Based Pedestrian Safety Process (Kumfer et al., 2018)	Segments, Seattle, Washington	Crashes, exposure, roadway	SPFs, empirical Bayes	GIS-based tool for screening and ranking segments, countermeasures
Pedestrian and Bicycle Crash Risk and Equity: Implications for Street Improvement Projects (Lindsey et al., 2019)	Roads and intersections, Minneapolis, Minnesota	Crashes, exposure, roadway, intersection	Negative binomial regression	Ranking and scoring of locations reevaluated to emphasize safety and equity
Risk Factors for Pedestrian and Bicycle Crashes (Monsere et al., 2017)	Segments and intersections, Oregon	Crashes, exposure, roadway, intersection	Logistic regression	Risk-scoring tool
Statewide Bicycle and Pedestrian Systemic Safety Analysis 2020 (Iowa DOT, 2020)	Segments and intersections, Iowa	Crashes, roadway, intersection	Crash rates, normalized and weighted by attribute	Composite scoring and mapping tool

2.2.2 Discussion

While the above recommended practices have their differences, they all work around similar core principles. What differences do exist between documents help to provide more options and ideas to those planning their own systemic safety analysis study. The variations in the results of this process may be seen in the example case studies. Each of the reviewed studies are similarly based on the recommended practices but have been tailored to the specific needs of each project. However, throughout these studies, some common limitations can be found. Ideas on how to overcome these obstacles are discussed near the end of this section.

2.2.2.1 Recommended Practices

All four of the recommended practice articles reviewed utilize the same core principles (detailed in the following paragraphs): defining the scope, collecting the data, analyzing the data to determine significant risk factors, and selecting treatment sites and appropriate countermeasures.

Each recommended practice document suggests beginning by defining the scope for a project. This step establishes the need to define most, if not all, of the following: geographic area, crash types, facility types, measures of exposure, and risk factors. These definitions will shape the rest of the project and should be as specific or as broad as the project requires. If necessary, these definitions may be reevaluated if they are later found to constrain or insufficiently bound the project.

With the scope firmly defined, the recommended practices continue with the data requirements. The required data can be separated into three classifications. Crash characteristics data include information pertaining to the type of crashes defined in the scope and commonly include crash type, crash severity, crash location, and other relevant data. Location characteristics data similarly include relevant information about the locations in the scope such as facility type, roadway features, and intersection features. Traffic characteristics data mostly includes exposure or traffic volume data for vehicles, bicycles, and pedestrians as required by the scope. Once collected, most articles suggest that all relevant data should be compiled into a database.

Once the data have been collected, the articles present various options for how data analysis takes place. All agree that risk factors should be determined, but a variety of methods have been proposed. These methods include options such as taking risk factors from related literature or determining them as part of the project scope. Most commonly, risk factors are derived from statistical or regression models using the collected data, such as the estimation of negative binomial regression models or the development of safety performance functions through this process.

Finally, the risk factors are used along with the collected data to identify possible locations in need of treatment. Often, risk factors receive scores or points are assigned, and locations are ranked. Additionally, appropriate countermeasures are selected to mitigate the risk factors. With the analysis complete, the necessary countermeasures can be deployed at the prioritized sites displaying the risk factors.

Other important similarities between the recommended practices are the benefits of using a systemic analysis. One of these benefits is the effective use of resources. Generally, the systemic approach yields countermeasures that have a higher benefit-to-cost ratio when compared to results of the crash-based approach. The articles also agree that this type of data-driven approach creates a stronger basis for making decisions due to its reliance on data and objective analysis. Systemic analysis is also seen as a more proactive approach based on site-specific features related to crash risk (before crashes occur) as opposed to the reactive approach of addressing observed crashes (after they have occurred). This approach is also considered more consistent as all potential problems may be identified and treated as opposed to only those which have already caused trouble.

Despite the many similarities between the recommended practices, there are some important differences as well. In the “Guide for Scalable Risk Assessment Methods for Pedestrians and Bicyclists” (Turner et al., 2018), there is no step for evaluating the effects of a project. This may be because the guide focused more narrowly on the risk assessment process and assumed that standard methods for project evaluation would be used in later steps. Several other differences can be found in “Reliability of Safety Management Methods: Systemic Safety Programs” (Gross et al., 2016). Unlike the other articles, this one is focused less on the steps to implement a systemic analysis and more on how to integrate this method into existing programs and improve the systemic approach itself. As previously mentioned, two variations of the systemic approach (benefit-cost threshold, and hybrid systemic and crash based) are subsequently given. While these variations may conflict somewhat with the other articles, they also show that a systemic approach can be altered to fit the requirements of a given project and fit within existing agency safety management processes.

2.2.2.2 Case Studies

Each of the reviewed case studies made similar use of the recommended practices. When defining each project scope, a crash type of either all crashes involving bicyclists and pedestrians or only crashes with fatal or serious injury was used. While all used pedestrian-related crashes, most also used those crashes involving cyclists. The majority of these cases further defined their scope by looking at these crashes only on a specific road type (such as highways or arterials) in their region, or a selection of roadway segments and/or intersections.

The case studies also used similar sources and types of data. All relied on data from existing databases and linked crash data to the corresponding roadway segment or intersection if the connection did not already exist. Most studies used vehicle traffic volume data in their analysis. Several of the studies also accounted for bicycle and pedestrian volumes in some way, although others mentioned the difficulty of obtaining such exposure data. Examples of more-or-less direct measures of exposure include cyclist and pedestrian volume data, land-use data, or US Census data. Some studies had broad definitions when collecting their data while others were more restrictive.

Every study encountered data limitations of some kind, most of which involved a limited amount of or a complete lack of data in some categories. Several methods were used to combat this problem. Case Example 2 "formed an expert panel to help identify key risk factors to use in subsequent steps in the analysis" instead of relying on analysis of their collected data (Thomas et al., 2018). Several used US Census and land-use data to aid in their estimations of bicyclist and pedestrian exposure when volume data was limited. Other studies made note of the limited bicyclist and pedestrian exposure data and said more work would need to be done at treatment sites to determine which had a high enough exposure to warrant treatment.

For data analysis, negative binomial (NB) regression, which is used on highly variable crash data, was employed by most of the studies. However, a variety of methods were used by the studies to help before or after implementing this type of analysis. For example, Case Example 1 used an empirical Bayes ranking method after NB regression (Thomas et al., 2018). On the other hand, the study by Kumfer et al. (2018) used conditional random forest regression before their NB regression analysis to prepare the data. However, case studies three and four did not use any NB regression, and instead, respectively, used risk scores from safety literature or created their own matrix.

All the case studies produced similarly useful results, but with a variety of final products. Some created tools for finding problem locations and determining the proper countermeasures to employ. Several of these studies created GIS-based tools to help simplify the process of selecting treatment sites. Other studies simply determined which locations needed further examination where countermeasures should be implemented.

As with the articles on the recommended practice, there were some differences between the case studies examined. When determining scope, most of the studies used all roads of a designated type in their geographic area. Case Example 1 and Monsere et al. (2017) were much more selective, either purposefully choosing or randomly selecting a number of intersections and segments in the study area. Both of these studies did so in order to limit the overall scope of the study. Some studies also used different methods to acquire and analyze data. Monsere et al. (2017) found a unique approach to overcoming their data limitations by using data from Strava to supplement bicycle exposure data. Case Example 2 first used a crash-based analysis, then a risk-based analysis, with similar results. Case Example 4 was unique in creating a crash and facility types matrix to determine their risk scores (Thomas et al., 2018). Further differences arose in how the results were implemented. Lindsey et al. (2019) used their findings to reevaluate project rankings to emphasize safety and equity, and Monsere et al. (2017) also revisited and reconsidered previously selected projects. On the other hand, Kumfer et al. (2018) produced two new SPFs for use in a screening process.

2.2.2.3 Existing Limitations

In reading these articles and studies, a number of limitations may be noted. First, there is limited data on pedestrian and bicycle exposure, possibly due to the difficulty of collecting these data across many locations. Another difficulty is that what exposure data is available typically has not been collected for an extended period of time. More limitations exist in the relatively small number of systemic studies on pedestrian and bicycle safety that have been completed. Until more of these studies are finished, their overall effectiveness and impact is largely unknown. Another reason to conduct more systemic safety studies is that many crash modification factors (CMFs) reflect safety effectiveness for crash-based projects and have unknown effectiveness for systemic projects.

Other limits on systemic studies come from those carrying out the studies. Some of the studies reviewed were seen by those conducting them as one-time projects instead of a cyclical program to be constantly reevaluated to find new potential treatment sites. Another issue is viewing systemic programs as a replacement for crash-based projects. According to Gross et al. (2016), “crash-based and systemic safety projects are complementary, serving different purposes within an overall safety management program.”

2.2.2.4 Innovations for Utah

There are many ways these limitations could be addressed in Utah. To combat the limited amount of pedestrian and bicyclist exposure data, more data can be collected in a variety of ways. Pedestrian counters can be installed at intersections, bicyclist count studies can be carried out, and data can be obtained from secondary third-party sources such as Strava, pedestrian push-buttons at traffic signals, or mobile-device data. UDOT could even use their traffic app to have individuals report this information or collect it through their phone’s location services.

The state of Utah could also assist in evaluating the efficacy of systemic studies and existing CMFs by conducting more of these studies. However, doing so correctly is of the utmost importance. The cyclical nature of systemic projects needs to be emphasized to those working on these programs and in the literature derived from them. A systemic safety analysis cannot be a one-time effort, it should be periodically updated and refined as more data become available and as crash risks and scopes evolve. Additionally, studies that specifically combine (and compare) crash-based and systemic approaches would be helpful.

A number of suggestions are also given in Gross et al. (2016) which may be useful in Utah. The article emphasizes the need for agencies to track systemic projects so those wishing to evaluate them may more easily identify them. If possible, sample sizes should also be increased to use more reliable data analysis methods. As part of each systemic program, an analysis on fatal and serious injury crash reductions should be conducted for completing a cost-benefit analysis.

2.2.3 Conclusion

For this literature review, a number of recommended practice articles and case studies for the systemic approach to bicycle and pedestrian safety analysis were reviewed. The recommended practices may be summarized as defining the project scope, compiling data, analyzing data, selecting treatment locations and countermeasures, refining and implementing a treatment plan, and evaluating project impacts. A variety of case studies were examined with different project scopes, goals, and outcomes. Similarities and differences between the recommended practices and case studies have been examined, along with existing limitations and how these problems may be addressed in the state of Utah.

2.3 Risk Factor Identification and Modeling Methods

As described in the review of systemic safety analysis methods in Section 2.2, the identification of risk factors is a key step in the process and an important difference between the systemic approach and the traditional crash-based approach. As the recommended practices and case studies made clear, there are many ways to identify risk factors, ranging from determinations from expert knowledge or prior research, to simple-to-complex analytical methods based on crash and roadway data or models (Thomas et al., 2018). This section describes the common data-driven and modeling approaches and methods for analyzing and identifying risk factors for pedestrian and bicycle crashes. The following Sections 2.4 and 2.5 summarize the literature and what prior research says about pedestrian and bicycle crash risk factors.

2.3.1 Crash Frequencies

Crashes are rare events that occur with low probability to each individual road user on a particular trip. However, over many months/years and across many thousands of road users, those very small probabilities add up and result in crashes. Most studies that investigate risk factors for crashes use these aggregated counts of crashes (crash frequencies) as the outcome measure of interest. Crash frequencies are usually measured as the number or count of crashes or collisions that have occurred in a particular location—roadway segment or intersection—over a set time period. That said, not all crashes are reported to police (the major source of crash data), and less severe crashes are more likely to go unreported than fatal or serious injury crashes. Also, some crashes do not need to be reported in this way (e.g., crashes not involving a motor vehicle or not on a public roadway). Nevertheless, crash frequencies reported in state/federal databases are the most common sources of data that are used to determine risk factors.

For example, crash frequency is the typical variable used to evaluate pedestrian and bicycle safety. Many researchers have used the number of crashes that occurred in historical data to identify significant risk factors contributing to vehicle–pedestrian and vehicle–bicycle collisions in the US, Australia, and Canada (Wier et al., 2009; Schneider et al., 2010; Lee and Abdel-Aty, 2005; Chimba et al., 2014; Pulugurtha and Nujjetty, 2011; Torbic et al., 2010; Zegeer et al., 2001; Gårder, 2004; Miranda-Moreno et al., 2011; McMahon et al., 1999; Poch and Mannering, 1996). Sometimes, frequency is converted into a crash rate, another common dependent variable which depicts crash frequency per unit. Zegeer et al. (2006) collected the physical characteristics and behavioral data of 68 sites in California, Pennsylvania, and Florida. The number of pedestrian crashes per site per year was used as the dependent variable. Loukaitou-Sideris et al. (2007) used the number of fatal crashes per 10,000 population to analyze the influence of urban sprawl on pedestrian safety.

Instead of categorizing crash locations into midblock crossings and intersections and calculating crash frequencies for segments and intersections, some studies assigned crashes to areas or zones, with the most typical spatial structure being US Census tracts. Census tracts are a pre-defined spatial unit where many socio-demographic variables are available. Most of these studies focus on the relationship between pedestrian/bicycle safety and land-use characteristics.

For example, Wier et al. (2009), Jang et al. (2013), Chimba et al. (2014), Fitzpatrick et al. (2014), Gårder (2004), Loukaitou-Sideris et al. (2007), and McMahon et al. (2002) all developed models by using the crash data per unit area or for different Census tracts.

Two important characteristics of crash frequency data are that they are integers (one cannot have partial crashes) and that they are non-negative (one cannot have negative crashes). When analyzing bicycle and pedestrian crashes, another characteristic is relevant: Many locations (especially those outside of urban areas, or for shorter time frames) will have zero values. All of these characteristics complicate the analysis of these data. The following section describes different ways of analyzing crash frequency data, using linear regression, Poisson regression, negative binomial regression, and other methods.

2.3.2 Models of Crash Frequencies

2.3.2.1 Linear Regression

Regression methods are appropriate for identifying risk factors because they can estimate statistically significant associations between dependent variables—safety outcomes (crash frequencies)—and independent variables (potential risk factors). A simple regression model is linear regression, estimated using ordinary least squares. The dependent variable (crash frequency) Y_i at site i is modeled as a function of a linear combination of k independent variables (risk factors) X_{ki} and model parameters β_k, along with an error term ε_i that reflects unobserved contributing factors:

$$Y_i = \sum_k \beta_k X_{ki} + \varepsilon_i$$

When the regression model identifies a "statistically significant" independent variable X_k, it is saying that the data suggest that $\beta_k \neq 0$ and thus that the variable is associated (positively or negatively) with the dependent variable Y_i. In other words, there appears to be some sort of relationship between the risk factor variable and the crash frequency outcome; i.e., that variable may be a risk factor for crashes.

Linear regression has been used in some pedestrian and bicycle safety studies. Wier et al. (2009) used ordinary linear regression to build a model to estimate pedestrian crash frequency based on data from 2001 to 2005 in San Francisco. Zegeer et al. (2006) used a similar statistical model on pedestrian crash frequency rate at intersections. Linear regression models were used in some studies accompanied by another modeling approach. Dixon et al. (2012) used SPFs along with two types of linear regression models, urban and rural, in order to quantify safety performance along state highways. These SPFs were mainly focused and applied to vehicles (Dixon et al., 2012). Another study looking at predicting accidents for roads with minor junctions used a linear model in conjunction with an empirical Bayes procedure (Mountain and Jarrett, 1996).

A major drawback of linear regression is that it can predict negative crash frequencies in some situations. Another limitation is that it is based on distributions that contain continuous (not integer) values. Also, other key distribution assumptions used in linear regression may be violated by the unique characteristics of crash frequency data. As a result, most studies use a different type of regression: Poisson or negative binomial.

2.3.2.2 Poisson Regression

In contrast, Poisson regression is based on probability distributions and assumed data generating processes that are founded on counts of events that are integer and non-negative. Using the Poisson distribution, the probability that Y_i events (crashes) occur at site i during a given time period is given by:

$$P(Y_i) = \frac{e^{-\lambda_i}\lambda_i^{Y_i}}{Y_i!}$$

where λ_i is a rate parameter, interpreted as the average number of events (crashes) in that time period. To form a Poisson regression model, we predict the rate parameter (crashes per time) λ_i as a function of k independent variables (risk factors) X_{ki} and model parameters β_k, using a natural log transformation of the dependent variable:

$$\ln \lambda_i = \sum_k \beta_k X_{ki}$$

As in linear regression, a "statistically significant" independent variable implies that there seems to be a relationship between the risk factor variable and the crash rate outcome, and thus that the variable may be a risk factor for crashes. An important difference, though, is that due to the natural log transformation, the model can only predict non-negative rate values.

Poisson regression models have been used to analyze pedestrian/bicycle crash frequencies and to identify risk factors. Oh et al. (2008) used the Poisson distribution to analyze bicycle collisions at urban signalized intersections. Nordback et al. (2014) focused on finding SPFs for bicycles in cities in the United States, and used the Poisson distribution because of its ability to create a logical fit to the crash data. Finally, a Poisson model was used for a study of the largest cycling event held in New Zealand to determine what factors affect incident rates for bicyclists (Tin Tin et al., 2013).

One limitation of the Poisson regression model is that the mean and the variance of the outcome (crash frequency) variable must be approximately equal. This is often not the case with crash frequency data—given a large number of zeros and a long positive tail—and especially rare when dealing with pedestrian and bicycle crash data. Therefore, most scholars recommend using negative binomial regression instead.

2.3.2.3 Negative Binomial (NB) Regression

Negative binomial (NB) regression models are now common practice for modeling count or frequency data precisely because they can accommodate overdispersion: the tendency for a dataset's variance to exceed its mean. Since so many locations tend to have zero pedestrian or bicycle crashes, there is often an overrepresentation of zeros in a dataset, thus leading the mean to often be lower than the variance.

Using the negative binomial distribution, the probability that Y_i events (crashes) occur at site i during a given time period is given by:

$$P(Y_i) = \frac{\Gamma\left((1/\alpha) + Y_i\right)}{\Gamma(1/\alpha)Y_i!}\left(\frac{1/\alpha}{(1/\alpha) + Y_i}\right)^{1/\alpha}\left(\frac{\lambda_i}{(1/\alpha) + Y_i}\right)^{Y_i}$$

where λ_i is the same rate parameter as for the Poisson model (the average number of events in that time period), α is the overdispersion parameter (a measure of how overdispersed are the data), and $\Gamma(\cdot)$ is the gamma function: $\Gamma(z) = \int_0^\infty x^{-z-1} e^{-x} dx$. To form an NB regression model, as before we predict the rate parameter (crashes per time) λ_i (transformed using the natural log) as a function of k independent variables (risk factors) X_{ki} and model parameters β_k, and also an error term ε_i (gamma distributed with mean 1 and variance α) that reflects unobserved contributing factors:

$$\ln \lambda_i = \sum_k \beta_k X_{ki} + \varepsilon_i$$

As before, a "statistically significant" independent variable implies a relationship with the crash rate outcome, and thus a potential risk factor for crashes. An important difference, though, is that due to the gamma-distributed error term, the model can accommodate overdispersion (variance greater than the mean).

The appropriateness of NB regression for modeling bicycle and pedestrian count frequencies is illustrated by the many studies that have utilized it to estimate the crash rates of both intersections and segments in places such as the US, Canada, and Brazil (Schneider et al., 2010; Schneider et al., 2004; Chimba et al., 2014; Pulugurtha and Sambhara, 2011; Torbic et al., 2010; Zegeer et al., 2001; Poch and Mannering, 1996). Oh et al. (2008) considered an NB model when analyzing bicycle collisions at signalized intersections in an urban area. In a study that considered crashes involving a bicycle and motor vehicle at a signalized intersection, Wang and Nihan (2004) used three different NB models to estimate the risk of such collisions. Noland and Quddus (2004) used a fixed-effects NB model to analyze the risk factors of pedestrian and bicycle casualties for various regions in England. Finally, an NB regression model was used to study various factors, both road and bicycle, which influence bicycle risk factors at unsignalized intersections (Schepers et al., 2011).

2.3.2.4 Safety Performance Functions (SPFs)

The utility of NB models for crash frequency modeling is highlighted by the recommendation of the Highway Safety Manual (AASHTO, 2010) to use NB regression when developing safety performance functions (SPFs). SPFs describe a mathematical relationship between the frequency of crashes and the most significant risk factors for pedestrian and/or bicycle crashes. For example, an SPF for pedestrian crashes at intersections might look something like the following:

$$N_{base} = e^{(\beta_0 + \beta_1 \ln AADP + \beta_2 \ln AADP_{maj} + \beta_3 \ln AADT_{min})}$$

where N_{base} is the predicted crash frequency; $AADP$, $AADP_{maj}$, and $AADT_{min}$ are measures of exposure (annual average daily pedestrians or motor vehicle traffic volumes on the major or minor roadway); and $\beta_0, \beta_1, \beta_2, \beta_3$ are regression coefficients. Through a simple natural log transformation, this equation can be converted into the previous NB model crash rate equation.

Although SPFs for motor vehicle crashes are well established, SPFs for pedestrian and especially bicycle crashes are still being developed. One study used data at intersections in Boulder, Colorado, to create bicycle SPFs using an NB model (Nordback et al., 2014). In another study in Oregon, Dixon et al. (2012) illustrates a method of site selection, the collection of crash and site-specific data, and analysis method for calibration that is in line with the HSM's methods to quantitatively estimate three facility types: rural two-lane roads, two-way roads, rural multilane roads, and urban and suburban arterial roads. In Florida, Lu (2013) developed SPFs for various road types in order to compare different methods' performance and to identify high-crash locations. In Michigan, Dolatsara (2014) investigated factors that affect safety at intersections and found bicycle SPFs where exposure, the presence of bicycle lanes and bus stops, and the number of left-turn lanes at intersections are positively associated with bicycle crashes.

2.3.2.5 Other Methods

Some other quantitative methods have been used to analyze crash frequencies and determine risk factors. Sometimes study areas involve too few sites, too few crashes, or are missing data in ways that prevent a regression model from being developed. In these cases, a simpler tabular method can be used that sums up crashes, classifies those crashes by one or more characteristics, and identifies crash types or roadway/intersection conditions that are overrepresented (i.e., they have more than their share of crashes). Examples of this approach are documented in systemic safety guidebooks and case studies discussed in Section 2.2 (Preston et al., 2013; Thomas et al., 2018). The disadvantage of this is that potentially confounding factors (such as pedestrian, bicyclist, or motor vehicle traffic exposure) may not be accounted for.

On the other side, more complicated quantitative methods have occasionally been used to analyze crash frequencies and identify risk factors. One branch of this work uses machine learning (ML) methods to relax many of the restrictive parametric assumptions made in NB regression models. The variety of methods—decision trees, random forests, ensembles of models, neural networks—as well as the difficulty of easily interpreting model results has somewhat limited the use of ML methods in crash data analysis. However, these models (especially ensembles of models) can reduce prediction error, and some are able to provide interpretable results such as the most contributing risk factors affecting crashes and non-linear relationships: for example, a risk factor only influences crashes above a certain threshold level. Despite an increasing number of examples of ML studies in the safety literature (Abdel-Aty & Haleem, 2011; Karlaftis & Golias, 2002; Kashani & Mohaymany, 2011; Saha et al., 2015, 2018), only a few have investigated pedestrian and/or bicycle safety topics (Ding et al., 2018; Zhu, 2021; Shirani-Bidabadi et al., 2020). Future research should continue to investigate the applicability of ML methods for understanding bicycle and pedestrian crash risk factors.

2.4 Risk Factors for Pedestrian Crashes

The critical factors affecting pedestrian safety in terms of crash frequency are traffic volumes and characteristics, roadway geometric conditions, intersection geometric conditions, built environment and community variables, and weather and lighting. Roadway geometry factors include lane width, number of turn lanes, presence of shoulder, median, rumble strips, horizontal curvature, and vertical grades. Traffic variables include factors like traffic volume, pedestrian exposure, speed limit, traffic composition such as heavy truck percentage, and transit stops including bus stop and rail stations. Items related to community characteristics and land-use information include residential density, employment density, household income, number of vehicles per household, and other demographic characteristics such as race/ethnicity. Additional risk factors like weather information or lighting condition are also common attributes that are linked with pedestrian crash risk.

2.4.1 Road Geometry Characteristics

Major arterials and roadways with more lanes are associated with a greater number of pedestrian crashes (Chimba et al., 2014; Ukkusiri et al., 2012). Diogenes and Lindau (2010) also found higher vehicle–pedestrian crash frequencies at midblock crossings for wide roadways. Moreover, Palamara and Broughton (2013), Aziz et al. (2013), and Wang et al. (2006) came to similar conclusions that streets with more lanes lead to increased pedestrian crashes at midblock crossings and at intersections. Abdel-Aty et al. (2007) informs that having a wide road with a greater number of lanes near a school increases the risk of pedestrian crashes, and traffic calming measures such as road narrowing may improve pedestrian safety. However, crashes may commonly occur at urban streets with fewer lanes, according to Sandt and Zegeer (2006).

Steep grades are found to be negatively associated with pedestrian crashes at mid-block locations (Chen & Zhuo, 2016). This may happen due to pedestrians' tendencies to avoid steep streets due to the possible physical strain. On the other hand, Poch and Mannering (1996) highlighted the uphill or downhill grades, and an intersection approach may increase the likelihood of pedestrian crashes because of drivers' shortened sight distance and visibility. These findings suggest that the impact of grade on pedestrian crashes may be context-specific.

Harkey et al. (2006) found that the presence of turn lanes indicated an increasing pedestrian crash frequency. Left-turn movements or right-turn-on-red movements may create problems for crossing pedestrians at intersections, as drivers are focused on vehicles coming from the opposite direction. Schneider et al. (2010) found that a significantly greater number of pedestrian crashes occurred at intersections with more right-turn-only lanes. However, researchers also found that turning radius may have an impact on pedestrian crash occurrences as a smaller radius might decrease the probability of right-turn pedestrian injuries (Roudsari et al., 2004).

Frequent driveways can present additional conflict points between vehicles and pedestrians and thus create safety challenges. Schneider et al. (2004), Taquechel (2009), and Kim and Ulfarsson (2019) found that frequent driveways within 50 feet of intersections may lead to increasing numbers of pedestrian crashes, especially near downtown and commercial areas.

Dumbaugh et al. (2013) found that pedestrians are particularly vulnerable at uncontrolled driveways.

2.4.2 Intersection Characteristics

More legs at intersections provide greater numbers of crossing stages for pedestrians. Prior studies found that increasing the number of approaches at intersections was associated with a greater likelihood of pedestrian crashes (Schneider et al., 2010; Lee et al., 2019). Dumbaugh et al. (2013) estimated an NB crash prediction model and concluded that three-or-fewer-leg intersections have no significant effect on pedestrian crashes, while four-leg intersections create safety challenges for pedestrians.

Medians can offer refuge for pedestrian crossings and provide a comfortable crossing time, thus improving traffic safety for pedestrians at both signalized (Petritsch et al., 2005) and unsignalized intersections (Harwood et al., 2008). Schneider et al. (2010) found that raised medians on both major and minor legs were associated with lower numbers of pedestrian crashes. Palamara and Broughton (2013) highlighted the importance of medians in a study investigating pedestrian crash countermeasures in Perth, Australia. Zegeer et al. (2006) reached a similar conclusion that median islands at intersections may lead to lower pedestrian crash risk on wide multilane roads. Medians can provide improved safety conditions for pedestrians at mid-block sites as well; Baltes and Chu (2002) found that medians are associated with fewer crashes at mid-block locations.

2.4.3 Traffic Characteristics

More traffic on streets and intersections results in a greater exposure to motor vehicle traffic for pedestrians and thus is likely to cause a greater number of collisions. Traffic volume is often found to be a significant variable affecting the likelihood of pedestrian crash frequency and injury collisions. Schneider et al. (2004), Zegeer et al. (2006), Martin (2006), Loukaitou-Sideris et al. (2007), Weir et al. (2009), Pulugurtha and Sambhara (2011), Palamara and Broughton (2013), and Miranda-Moreno et al. (2011) all verified this statement and concluded that streets and intersections with higher traffic volumes are prone to see greater numbers of pedestrian crashes. However, a negative association between traffic volume and pedestrian crashes is possible since that higher amount of traffic on roads may lead to reduced speeds and thus create less risky situations for pedestrians, according to Chen and Zhuo (2016). In many cases, the rate of increase is steeper at a lower average traffic volume, as pointed out by Abdel-Aty and Keller (2005).

Torbic et al. (2010) estimated that the traffic volume of major roads and minor approaches at an intersection are significant variables for pedestrian crashes. Miranda-Moreno et al. (2011), Pulugurtha and Sambhar (2011), and Siddiqui et al. (2012) also found that traffic volume is a common predictor of crash frequency at intersections, and an increase in traffic volume is associated with diminished pedestrian safety. Zegeer et al. (2005) found that high traffic volume at unsignalized intersections leads to increased fatal pedestrian crashes.

Similarly, the likelihood of pedestrian crashes increases when the pedestrian volume increases, because (collectively) pedestrians would have more exposure to traffic. McMahon et al. (1999), Schneider et al. (2004), and Pulugurtha and Sambhara (2011) support this conclusion using exposure data at intersections. Pedestrian volume is also positively associated with a greater number of pedestrian crashes at intersections and at uncontrolled crossings of arterial and collector roadways (Harwood et al., 2008; Petrisch et al., 2005).

However, findings from prior studies also showed a negative association of pedestrian crash rates with traffic volume, indicating that because of more pedestrians' presence on roads, they may be more visible to motorists (Chen & Zhuo, 2016; Singleton, Mekker, & Islam, 2021). These results are reflections of the theory of "safety in numbers": where an increase in pedestrian and bicycle volumes are possibly associated with increased caution among motorists when more people are walking or bicycling. As a result, pedestrian and bicycle crash rates (crashes per pedestrian or cyclist) decrease with increasing pedestrian and bicycle volume (Jacobsen, 2003; Elvik & Bjornskau, 2017; Singleton, Mekker, & Islam, 2021).

Bus stop density is positively associated with pedestrian crash frequency (Miranda-Moreno et al., 2011; Ukkusuri et al., 2012; Wang & Kockelman, 2013; Chen & Zhou, 2016). Streets and intersections with higher public transit use are often located in highly urbanized areas with concentrated activities and may thus be more likely to experience crashes. Diogenes et al. (2010) pointed out that the high public transit vehicle volume would lead to more pedestrian crashes at midblock crossings. Also, the location of bus stops (on the near side or the far side of the intersection) and stopped buses may block pedestrians' sights when crossing streets. Schneider et al. (2004) and Diogenes et al. (2010) reported that midblock crossings near public transit stops and other public transit system facilities may lead to high pedestrian crash rates. Studies investigating both microscopic and macroscopic crash frequency modeling report that streets and intersections in areas closer to public transit stops are likely to experience more crashes (Amoh-Gyimah et al., 2016; Lee et al., 2017). Torbic et al. (2010) and Miranda-Moreno et al. (2011) found higher pedestrian crashes near intersections with frequent transit stops.

In most studies, the likelihood of a severe pedestrian crash increases with higher vehicle speed limits (Lee & Abdel-Aty, 2005; Zegeer et al., 2006; Chimba et al., 2014; Fridman et al., 2020). The severity of a pedestrian–vehicle crash increases substantially, since the risk of a pedestrian death from a crash at high speed is much greater compared to low speeds (Sze & Wong, 2007; Wang & Kockelman, 2013; Olszewski et al., 2015; Doecke et al., 2018). Although Senserrick et al. (2014) found that most pedestrian crashes occur not in low-speed urban areas but in high-speed rural areas, a negative association with high speed limit and pedestrian crashes is also found in the literature, as pedestrians may avoid high speed streets (Miranda-Moreno et al., 2011; Moudon et al., 2011; Narayanamoorthy et al., 2013).

2.4.4 Built Environment and Community Characteristics

Land-use type is a common variable linked with pedestrian crashes. Land-use variables can be used as potential proxy variables indicating pedestrian activity levels and interactions with other traffic. Pedestrian crashes may occur predominantly in mixed land-use areas (Chen & Zhou, 2016). This may happen because of the fact that mixed land-use areas are trip generators for pedestrian activities including neighborhoods, commercial buildings, community centers, schools, churches, playgrounds, etc. Pulugurtha and Sambhara (2011) made the conclusion that land-use predictor variables such as a single-family residential area, urban residential–commercial area, commercial center area, and neighborhood service district have a negative effect on pedestrian crashes in a given area. This may occur due to the presence of low traffic volumes and low-speed roads near residential areas. Thus, the relationship between crashes and neighborhood land use is complicated by pedestrian volume/exposure.

However, this finding is not uniform as residential areas are also observed to be associated with increased pedestrian crashes, as they can be a source of greater pedestrian presence on roads (Loukaitou-Sideris et al., 2007; Siddiqui et al., 2012). Wier et al. (2009) found that the shares of neighborhood commercial land area and residential–neighborhood commercial land area were positively associated with pedestrian crashes. Ding et al. (2018) studied pedestrian crashes to investigate built-environment effects and found that compact development areas with greater household density were related to increasing pedestrian crash rates.

Wier et al. (2009) estimated a macro-level pedestrian crash prediction model and found that employment density was positively associated with pedestrian crash frequencies using crash data from San Francisco. Noland and Quddus (2004), Johnson et al. (2004), Loukaitou-Sideris et al. (2007), and Amoh-Gyimah et al. (2016) found similar results, with a higher likelihood of pedestrian crashes in neighborhoods with high population and employment density. Miranda-Moreno et al. (2011) estimated a positive association of employment density and crash frequency in their models. They also introduced the number of jobs as a variable, and it had a similar effect as employment density.

A positive association of pedestrian crashes and areas with low income and/or minority populations has been supported by several previous studies (Dougherty et al., 1990; Laflamme & Diderichsen, 2000; Loukaitou-Sideris et al., 2007; Lyons et al., 2008; Cottrill & Thakuriah, 2010). Ukkusuri et al. (2011) showed a significant positive correlation between pedestrian crash frequencies and African-American or Hispanic neighborhoods, as well as populations with lower educational attainment. Chimba et al. (2014) and Amoh-Gyimah et al. (2016) found that higher rates of crashes were associated with lower household income. Torbic et al. (2010) also had similar findings regarding household income and pedestrian crashes. Wier et al. (2009) focused on the percentage of people living below the poverty level and drew the same conclusion. Jang et al. (2013), Chimba et al. (2014), and Loukaitou-Sideris et al. (2007) reported that people who identify as Latino, Black and Hispanic were more likely to be involved in pedestrian-vehicle crashes.

Household vehicle ownership was found to have a negative association with pedestrian crashes (Siddiqui et al., 2012, Chimba et al., 2014). It is likely because more vehicles in a household could be an indication of low pedestrian activity and less exposure to the risk of pedestrian collisions. Martin (2006) drew a similar conclusion in his review of pedestrian safety studies.

2.4.5 Weather and Lighting Conditions

Road lighting relates to drivers' sight and visibility directly and is thus a serious risk factor in pedestrian crashes. Fitzpatrick et al. (2014) indicated that 82% of the crashes in Texas from 2007 to 2011 occurred in dark conditions, almost half of which were at locations with no lighting. Senserrick et al. (2014) claimed that males and older pedestrians are more likely to be involved in crashes in poorer lighting conditions, particularly when crossing a road away from an intersection. However, Palamara and Broughton (2013) pointed out that the majority of pedestrian crashes occurred during daylight hours in central business district areas. Lee and Abdel-Aty (2005) and Jang et al. (2013) included the weather factor in the models and found that rainy weather had a positive influence on pedestrian crash frequency. However, due to the long time frames of most crash frequency models, weather effects are rarely used in applied models.

2.4.6 Summary

The following list summarizes the risk factors identified by the literature review as being associated with either more (positive association) or fewer (negative association) pedestrian crashes:

- Factors associated with more pedestrian crashes (positive association)
    - More lanes
    - Wider roadway
    - Major arterials
    - More turn lanes
    - More driveways
    - More approaches/legs
    - More motor vehicle traffic
    - More pedestrians (although the "safety in numbers" effect results in decreasing crash rates as pedestrian exposure increases)

- More bus/transit stops
  - Denser and more mixed-use areas
  - Areas with larger low-income populations
  - Areas with larger racial/ethnic minority populations
- Factors associated with fewer pedestrian crashes (negative association)
  - Steeper grades
  - Medians
  - Areas with greater household vehicle ownership
  - Daytime and well-lighted areas

2.5 Risk Factors for Bicycle Crashes

The critical factors affecting bicycle safety in terms of crash frequency are mostly the same as pedestrian risk factors described in the previous section: traffic volumes and characteristics, roadway geometric conditions, intersection geometric conditions, built environment and community variables, and weather and lighting. Additional bicycle-specific risk factors include the presence of bike lanes and bicyclist exposure.

2.5.1 Road Geometry Characteristics

Road geometry plays an important role in bicycle crashes with other traffic. Researchers report that bicycle infrastructures such as bike lanes, protected bike lanes, and cycle tracks are effective in reducing bicycle injury crashes especially in roadways with lower AADT (Park et al., 2015; Pedroso et al., 2016; Poulos et al., 2015; Pucher & Buehler, 2016; Teschke et al., 2012). Although facilities such as bike lanes may encourage more cyclists on roadways, these facilities may not lead to an increase in crashes (Harris et al., 2013; Reynolds et al., 2009). Moreover, the configuration of nearby intersections and traffic volumes affects the usefulness of bike lanes. Bike lane width can also affect cyclists' safety since bike lanes 4–8 feet in width are found to have improved safety effects and lower crash numbers (Park et al., 2015). This may be because motorists tend to view bike lanes with traditional lane width as another vehicle lane or parking area, according to Toole (2010). Reynolds et al. (2009) and Raihan et al. (2019) found the presence of off-road bike paths improves the safety condition but cautions against mixed traffic of cyclists and pedestrians on sidewalks and multi-use trails as they may present a higher crash risk. However, the "dooring effect" for bike lanes parallel to street parking can be a regular source of severe bike crashes (Schimek, 2018; Bhatia et al., 2016).

Travel lane width on roadways has a nonlinear effect on bicycle safety. Sadek et al. (2007) found that when bike lanes are present, drivers may be more aware of bicyclists in the bike lanes and drive more cautiously to avoid collisions in narrow lanes. In fact, for specific roadway conditions (such as the presence of shoulders), narrow lane width can provide better safety conditions for cyclists than roadways with wider lane widths (Gross et al., 2009). On the other hand, in mixed traffic without bicycle facilities, narrow roads may lead to vehicles passing cyclists closer, which may present more risk (Walker, 2007). Petritsch et al. (2006) found that the more lanes there are on the roadway, the more motorists focus on the opposing travel lanes and turning traffic. Moreover, crashes occurring at less busy local roads or multi-use paths can be more severe, as found by Cripton et al. (2015). Haleem and Abdel-Aty (2010) considered the effect of turning traffic on bike crashes and found that the number of left-turn movements on both the major and minor approaches were significant factors that influenced bicycle risk.

Rumble strips are a proven countermeasure that reduces motor vehicle departure from traffic lanes. Findings in traffic safety literature suggest that rumble strips are effective in reducing bicycle crash rates as well (Garder, 1995; Elefteriadou et al., 2001; Spring, 2003; Torbic et al., 2003; O'Brien et al., 2014). Zebauers (2005) found that in a passing condition with cars, bicyclists get additional clearance on streets with rumble strips compared to streets where no rumble strips are present.

Greater shoulder pavement width may have a positive impact on cyclist safety since it is associated with decreased crash rates (Klop & Khattak, 1999; Abdel-Rahim & Sonnen, 2012). Shared markings in the middle of the travel lane tend to encourage cyclists to adjust positions away from the curb and towards the center of the road, increasing their visibility. Wide curb lanes were found to have similar effects as bike lanes and can potentially mitigate crashes caused by drivers overtaking cyclists riding in the street, by allowing more space for passing within the lane (Hunter et al., 1999; Metroplan Orlando, n.d.).

Horizontal and vertical curves are found to be contributing factors in bicycle collisions. Moore et al. (2011) found that crashes on curves or roadways with elevation cause more severe injuries for people bicycling. Kim et al. (2007) found that curved rounds significantly increase the chance that a fatal or incapacitating injury will occur during a vehicle-bicycle accident.

2.5.2 Intersection Characteristics

Intersection safety for people bicycling is influenced by vehicle volume, the presence of heavy vehicles, and speed limit on the major and minor roads (Dixon et al., 2012). Several studies found an increased risk of collisions at intersections compared to other road sections (Chen et al., 2012; Kaplan & Prato, 2015; Romanow et al., 2012; Stone & Broughton, 2003; Wei & Lovegrove, 2013). The configuration and design of intersections greatly influence bicycle crashes, as pointed out by Wang and Nihan (2004). Vandenbulcke et al. (2014) discussed that complicated rights-of-way at intersections, as well as larger and complicated designs at intersections, are a common source of danger for cyclists. The number of legs in an intersection is related to variations in crash frequency as studies show a greater number of legs are associated with an increase in bicycle crashes (Wang et al., 2017; Dumbaugh & Li, 2010; Strauss et al., 2013).

While bicycle paths and bike lanes are found to generally improve safety in busy urban areas, Prati et al. (2018) found that they might increase the risk of collisions at intersections. Kaplan and Prato (2013) posited that discontinuity points (i.e., intersections and roundabouts) in urban areas with a widespread bicycle infrastructure increased the risk of collisions. However, Chen (2015) stated that closely spaced intersections might also reduce the speed of road users which, in turn, let road users have more time to scan the environment and increase the probability to detect cyclists, thereby reducing the risk of collision. As a countermeasure, the implementation of speed-reducing measures such as speed humps at unsignalized intersections has proved to prevent 2.5% of cyclist fatalities, as found by Schepers et al. (2017). According to the literature, while roundabouts increase safety conditions for other types of road users, they may have an unfavorable effect on cyclist safety, sometimes leading to an increased risk of crashes when they replace other types of intersections (Poudel & Singleton, 2021; Hels & Orozova-Bekkevold, 2007; Daniels et al., 2008; Møller and Hels, 2008; Reynolds et al., 2009).

Wide medians at intersections are negatively associated with the likelihood of bicycle crashes. Medians and two-way turn lanes often coincide at an intersection and they are associated with reduced bicycle crashes (Zegeer et al., 2006; Scheperset al., 2011). Wide medians are often found to be associated with low crash rates (Saha et al., 2015; Stamatiadis et al., 2009). On the other hand, Park et al. (2015) discussed that in a crash association study, higher median width may indirectly reflect chances of conflicts between bikes and vehicles, as wide medians are commonly present in roadways with multiple lanes and high-volume traffic.

The number of driveways near intersections is a statistically significant factor that influences the risk level of bicyclists, as found by Oh et al. (2008). Pulugurtha and Thakur (2015) suggested that limiting driveways to less than 50 per mile can reduce occurrences of bicycle crashes. Others (Gill, 2007; Davis & Hallenbeck, 2008; Shah et al., 2021) found that low driveway density especially near intersections and also along mid-block locations present lower risk to bicyclists.

2.5.3 Traffic Characteristics

Dense motor traffic volume causes an increased number of crashes for cyclists at intersections (Vandenbulcke et al., 2014; Kim et al., 2007). Lee et al. (2017) found that traffic volume on both major and minor legs at an intersection had positive and significant impacts on bicycle crashes at intersections, however the traffic volume on the major road had a larger impact on crashes. Nordback et al. (2014) also found that bicycle crashes were sensitive to traffic volume. Dixon et al. (2012) presented that high traffic volume in an urban setting is associated with a greater number of bike crashes. At intersections, Haleem and Abdel-Aty (2010) considered the effect of turning traffic on bike crashes and found that the traffic volumes on the major and minor approach, as well as the distance to the nearest signalized intersection, were significant factors that influenced bicycle crash risk.

The presence of public transit stops such as bus stops, light rail, and commuter rail stations are often associated with greater numbers of bicycle crashes, since frequent bicycle activity may be centered around such stations (Morrison et al., 2019). In particular, previous studies found bus stops and bus transit intensities as being significant factors associated with the presence of bicycle collisions (Quddus, 2008; Cho et al., 2009). Near intersections, the presence of a bus stop attracts more bicyclists and can contribute to more bicyclist injuries, as found by Strauss et al. (2013)

Studies have found decreased crash rates along road segments where the speed limit is greater. However, it does not mean that high speeds are safer; rather, higher-speed roads tend to have fewer vulnerable road users (Griebe 2003; Morrison et al., 2019). Wang and Nihan (2004) also found that lower speed limit is associated with lower risk for bike crashes, but state that it could be related to the maneuvers of right-turning vehicles. Alternatively, a greater body of research has found that higher speed limits lead to worse injury severity levels (Haleem & Abdel-Aty, 2010; Kim et al., 2007; Cripton et al., 2015) and more frequent crash occurrences (Eluru et al., 2008; Zahabi et al. 2011; Kim et al., 2007).

Bicyclists may also show avoidance behavior for streets with higher percentages of heavy trucks. Large vehicles' presence can significantly affect bicyclists' levels of comfort, and they tend to avoid streets with higher percentages of heavy trucks, as found by Pokorny and Pitera (2019). These concerns are well-founded since, when large vehicles such as trucks are involved in a vehicle–bicycle crash, cyclists are more likely to be severely injured both at mid-block locations and at intersections (Moore et al., 2011; Yang et al., 2015; Kim et al., 2007; Walker, 2007; Boufous et al., 2012).

In crash analysis, bicycle exposure has been incorporated in the form of bicycle counts from automated count stations or human counts (Guo et al., 2018; Prato et al., 2016), as well as bicycle trip estimation by fitness apps such as the Strava Metro app (Chen et al., 2020; Raihan et al., 2019; Sanders et al, 2017) based on the assumption that Strava counts are distributed evenly among total bicycle road users. However, accurate and complete bicycle exposure is difficult and time consuming to collect as manual collection of non-motorized volume can present significant error (Nordback et al., 2013; Chen et al., 2020; Roll, 2013), and bicycle app counts represent a low percentage of actual bike trips, as pointed out by Saha et al. (2018). Authors have attempted to account for bicycle exposure using macro-level spatial information such as density (Lee et al., 2017).

Studies have found that bicycle exposure estimated from the Strava app is associated with increasing crash rates (Chen et al., 2020; Saad et al., 2019). Schepers et al. (2011) reported that unsignalized intersections with high bicycle volumes were associated with more crashes. However, there are also a number of studies that suggest a phenomenon of "safety in numbers" for cyclists, since a greater number of cyclists on the road yields lower crash rates and contributes to an overall safety improvement for all road users, as discussed by Marshall and Garrick (2011). In a broader trend, safety-in-numbers effects are a common finding across different cities and regions, but the reasons behind it are incompletely known, and there are variations in the strength of the safety-in-numbers effect (Kröyer, 2015; Daniels et al., 2011; Elvik & Bjornskau, 2017).

2.5.4 Built Environment and Community Characteristics

Land use and community characteristics have an impact on bicycle crashes because, depending on land-use characteristics, road segments and intersections can face varying levels of bicycle trips and crashes. As expected, urban road network density is associated with more bicycle crashes, and rural road network density is associated with fewer bicycle crashes (Saha et al., 2018; Noland & Quddus 2004). Greater intersection density is also associated with increased bicycle crashes, indicated by Wei and Lovegrove (2013). Sando and Moses (2011) found that the number of intersections per mile increases the number of bicycle crashes. Moreover, Pulugurtha and Thakur (2015) suggested that limiting the number of unsignalized approaches to less than 10 per mile and increasing the spacing between signalized intersections may help to reduce the number of bicycle crashes.

Wier et al. (2009), Pulugurtha and Sambhara (2011), and Ukkusuri et al. (2011) showed that land-use patterns could influence the occurrence of crashes for non-motorized users such as bicyclists. Ladron de Guevara et al. (2004), Lee et al. (2015), and Loukaitou-Sideris et al. (2007) found that population density was positively related to bicycle crash counts.

Among community characteristics, median household income is negatively associated with crash frequency, as streets and intersections in areas with more lower income households tend to face more crashes (Huang et al., 2017; Lee et al., 2015; Martinez & Veloz, 1996). The fact that low-income areas lag behind in bicycle and pedestrian safety is supported by numerous studies (Britt et al., 1998; Lyons et al., 2008; Siddiqui et al., 2012). Saha et al. (2018) estimated the relationship between bicycle crash risk and built-environment characteristics by accounting for partial autocorrelation across census block groups, finding that fewer automobiles in a household is found to be associated with increasing crash risk. This finding is similar to the study conducted by Loukaitou-Sideris et al. (2007). Siddiqui et al. (2012) found that neighborhoods with minority populations—including large proportions of Black or African-American populations and Hispanic or Latino populations—are associated with increased likelihood of bicycle crashes.

2.5.5 Weather and Lighting Conditions

Bicycle crashes are inherently influenced by specific sets of factors like weather. Bad weather such as fog, snow, or rain is an impactful factor as they contribute to higher bike crashes (Mohan et al., 2006; Stone & Broughton, 2003). Research (Klopp & Khattak, 1999; Wanvik, 2009) recognizes that bad weather conditions and darkness increases the chances of bike crashes. Pai (2011) found that adverse weather and wet roads were the most common factors in rear-end bike crashes. Roadway lighting appears to have a substantial positive effect on cyclist safety at night (Kim et al., 2007; Chen & Zhuo, 2015; Eluru et al., 2008; Bíl et al., 2010). Boufous et al. (2011) found that a lack of visibility due to darkness increased crash frequency. However, as was mentioned for pedestrian crashes, weather/lighting effects are rarely considered in applied crash frequency models since they predict crashes over long time periods (a year or more).

2.5.6 Summary

The following list summarizes the risk factors identified by the literature review as being associated with either more (positive association) or fewer (negative association) bicycle crashes:

- Factors associated with more bicycle crashes (positive association)
    - Narrower lanes (without bicycle facilities)
    - Horizontal or vertical curves
    - Intersections
    - Roundabouts
    - More driveways
    - More approaches/legs
    - More motor vehicle traffic

- More turning motor vehicles
- More people bicycling (although the “safety-in-numbers” effect results in decreasing crash rates as bicycle exposure increases)
- More bus/transit stops
- Greater density of intersections
- Denser areas
- Areas with larger low-income populations
- Areas with larger racial/ethnic minority populations

- Factors associated with fewer bicycle crashes (negative association)
    - Bicycle infrastructure (such as lanes, protected lanes, and off-street paths)
    - Shared bicycle markings (“sharrows”)
    - Wider bike lanes
    - Wider shoulders or curb lanes
    - Narrower lanes (with shoulders)
    - Rumble strips
    - Wider medians
    - Areas with greater household vehicle ownership

2.6 Summary

This chapter summarized the practice of systemic safety analysis, methods for identifying risk factors, and specific kinds of risk factors—roadway, intersection, traffic, built environment, and other characteristics—associated with pedestrian and bicycle crashes. Relevant stages in systemic safety analysis include defining the project scope, compiling and analyzing data, and selecting treatment locations and countermeasures. The standard state-of-the-practice for identifying risk factors through data analysis is the use of negative binomial regression models.

A thorough review of the literature identifies similarities and differences in risk factors for pedestrian crashes compared to bicycle crashes. More pedestrian and bicycle crashes are expected in places with greater motor vehicle traffic, more driveways and turns, more transit stops, intersections with more approaches/legs, and in denser areas with larger low-income and racial/ethnic minority populations. Fewer pedestrian and bicycle crashes are expected in places with (wider) medians and in areas with greater household vehicle ownership. Unique to pedestrians, wider arterials with more lanes are associated with more crashes. Unique to people bicycling, rumble strips as well as bicycle infrastructure and facilities are associated with fewer crashes, and lane widths have a complex relationship. There appears to be a “safety-in-numbers” effect for walking and bicycling: while more pedestrian or bicycle traffic may lead to somewhat more crashes, the relationship is non-linear; more pedestrian or bicycle traffic would lead to decreasing crash rates (lower risk per person).

Knowledge of these systemic safety analysis methods and potential risk factors aids in the collection, assembly, and modeling of crash and other data that are presented in the following Chapters 3.0 and 4.0.

3.0 DATA COLLECTION

3.1 Overview

This chapter discusses the entire data collection and assembly process. First, the types of study locations (segments or mid-block locations, signalized, and non-signalized intersections) are defined. Next, the process of assembling crash data and exposure data are described, including visualizations of the resulting distributions. Then, information about data on roadway and community characteristics is presented. Finally, descriptive statistics for the resulting combined datasets are shown.

3.2 Study Locations

As described in Section 2.2, the first step of a systemic safety analysis is to define the study scope, including the specific geographic area and types of facilities or locations being studied. This project used the entire state of Utah as the geographic study area, and selected state highways (Interstate, US, and UT highways, with route numbers less than 1000) and local "federal-aid" roads and streets (FA highways, with 4-digit route numbers) as the roadway scope. Information was primarily available for state highways, while some information was available for some federal-aid highways. Little to no roadway information was available for local roads and streets, so they were not included in the scope of this project. Thus, there were two sets of locations, those on state routes (smaller sample size but more information) and those on state or federal-aid routes (larger sample size but less information).

Specific study locations were split into three types, depending on the roadway type and following common practices: segments or mid-block locations, signalized intersections, and non-signalized intersections. Details about each of these types of study locations are described in the following subsections.

3.2.1 Segments or Mid-Block Locations

Segments or mid-block locations include all locations where a crash occurred away from an intersection of two or more streets. To ensure relatively consistent spatial units between different datasets, segments were derived from the links in the "Road Centerlines" geodatabase, obtained in March 2020 from the Utah Geospatial Resource Center (UGRC) website (UGRC, n.d.). Segments were of varying lengths: mean 0.34 mi, median 0.13 mi, and middle 50% between 0.07 and 0.31 mi.

Many of these segments represented local streets, not portions of the state or federal-aid highway network. Segments on the state or federal-aid highway network were identified by route numbers less than 999 (state routes) or less than 9999 (state and federal-aid routes). Up to 13,107 state-only road segments and 46,497 state and federal-aid route road segments were initially investigated in this study.

3.2.2 Signalized and Non-Signalized Intersections

Intersections include all locations where a crash occurred at or very close to an intersection of two or more streets. Intersections can be signalized (controlled by a traffic signal) or non-signalized—controlled by one or more stop signs or yield signs. This report contains information and results for both signalized and non-signalized intersections; although signalized intersection crash frequencies were analyzed as part of a different UDOT research project (Singleton, Mekker, & Islam, 2021).

To ensure relatively consistent spatial units between different datasets, junctions were first derived from the nodes in the "Street Network" geodatabase, obtained in March 2020 from the UGRC website (UGRC, n.d.). The links in the "Street Network" geodatabase were compared to those in the "Road Centerlines" geodatabase and were found to be almost identical. Also, the locations of signals were obtained from the latitude and longitude information contained within a signals database shared by UDOT traffic signal staff in October 2019.

Some of these junctions were signalized intersections, so junctions were allocated between signalized and non-signalized intersections using the following heuristic processes. All thresholds were determined through trial and error and visual inspection of maps.

- Signals were spatially joined to the nearest junction and were matched unless one of the following conditions was true:
    - The distance from the signal to the junction was greater than 75 m.
    - The distance from the signal to the junction was greater than 25 m and the signal was likely to not be at an intersection (e.g., HAWKs, streetcar, fire station, flasher, gantry, queue, or lab).
- Junctions with a joined signal were assumed to be signalized intersections, while junctions without a joined signal were assumed to be non-signalized intersections.

A closer look at the geography of the junctions and the road network showed that some of the signalized intersections and many of the non-signalized intersections were located at the intersection of local streets, not on the state or federal-aid highway network. Therefore, junctions were linked to segments using the following heuristic processes. All thresholds were determined through trial and error and visual inspection of maps.

- Segments links were spatially intersected with shapes obtained from a 1 m buffer of junction nodes. In other words, all junctions and segments were matched if they were no more than 1 m away from each other.
- Junctions on the state or federal-aid highway network were identified by any matched segments with route numbers less than 999 (state routes) or less than 9999 (state and federal-aid routes).

Overall, up to 3,770 non-signalized intersections on state routes and 48,563 non-signalized intersections on state and federal-aid routes were initially included in this study. At the time of this study, there were up to 2,266 traffic signals installed across Utah. However, some of these were not connected to the central network or did not have pedestrian push-buttons (the source of the pedestrian exposure data), or were missing information on key independent variables (exposure, roadway and community characteristics), so the actual sample sizes used in the analyses were several hundred less.

3.3 Crash Data

Crash data for all study locations from 2010 through 2019 were obtained in August 2020 from the Utah Department of Transportation (UDOT) through the Numetric website (Numetric, n.d.). Each crash record contained information on temporal characteristics, spatial characteristics, contributing factors, crash severity, weather conditions, and crash participants. This information was extracted from police crash reports. No personally identifying information was included.

From the set of all crashes over the ten-year study period, bicycle and pedestrian crashes were extracted using the fields “bicycle involved” and “pedestrian involved.” Crashes were also segmented by severity, and fatal and serious injury crashes were extracted using the field “crash severity” and levels “fatal” and “suspected serious injury.” Next, crashes were assigned to segments or mid-block locations, non-signalized intersections, and signalized intersections using the following heuristic procedures. All thresholds were determined through trial and error and visual inspection of maps and crash records.

- Crashes with “false” for the field “intersection involved” were assumed to have occurred along segments or at mid-block locations.
    - These crashes were then spatially joined to the nearest segment with the same route number.
        - If the distance from the crash to the segment was less than or equal to 50 m, then the crash was assigned to that segment.
        - If not, then the crash proceeded to the following steps.
    - Remaining crashes were then spatially joined to the nearest segment, not matching on route number.
        - If the distance from the crash to the segment was less than or equal to 25 m, then the crash was assigned to that segment.
        - If not, the crash was discarded as being too far from a segment.
- Crashes with “true” for the field “intersection involved” were assumed to have occurred at non-signalized or signalized intersections.
    - These crashes were then spatially joined to the nearest junction and to the nearest signal.

        - If the junction was a signalized intersection, then the crash was assigned to that signal.
        - If not, then the crash proceeded to the following steps.
    - Remaining crashes with “signal” in the field “traffic control device” were assumed to have occurred at signalized intersections.
        - If the distance from the crash to the signal was less than or equal to 150 m (and no more than 75 m further away from the signal than from the junction), then the crash was assigned to that signal.
        - If not, for crashes with “ramp intersection with crossroad” in the field “roadway junction type” and if the distance from the crash to the signal was less than or equal to 300 m, then the crash was assigned to that signal.
        - If not, for crashes with “4-leg intersection” in the field “roadway junction type” and if the distance from the crash to the signal was less than or equal to 125 m, then the crash was assigned to that signal.
        - If not, then the crash proceeded to the following steps.
    - Remaining crashes without “signal” in the field “traffic control device” were assumed to have occurred at non-signalized intersections, with one exception:
        - If the distance from the crash to the signal was less than or equal to 75 m (and no more than 25 m further away from the signal than from the junction), then the crash was assigned to that signal.
    - Remaining crashes were then spatially joined to the nearest junction (with 3+ legs, and with 2+ legs) and with the same route number, as well as to the nearest junction (with 3+ legs, and with 2+ legs), not matching on route number.
        - If the distance from the crash to the junction with 3+ legs and the same route number was less than or equal to 100 m, then the crash was assigned to that non-signalized intersection.
        - If not, if the distance from the crash to the junction with 2+ legs and the same route number was less than or equal to 100 m, then the crash was assigned to that non-signalized intersection.

- If the distance from the crash to the junction with 3+ legs and the same route number was less than or equal to 200 m, then the crash was assigned to that non-signalized intersection.
- If not, if the distance from the crash to the junction with 2+ legs and the same route number was less than or equal to 200 m, then the crash was assigned to that non-signalized intersection.
- If the distance from the crash to the junction with 3+ legs and any route number was less than or equal to 100 m, then the crash was assigned to that non-signalized intersection.
- If not, if the distance from the crash to the junction with 2+ legs and any route number was less than or equal to 100 m, then the crash was assigned to that non-signalized intersection.
- If not, the crash was discarded as being too far from an intersection.

Figure 3.1 depicts a flowchart showing these steps to determine which pedestrian and bicycle crashes occurred at segments or mid-block locations, at non-signalized intersections, and at signalized intersections. Of the 7,658 pedestrian crashes and 6,448 bicycle crashes that occurred in Utah over the ten-year period from 2010 through 2019: 3,018 pedestrian crashes (39.4%) and 2,177 bicycle crashes (33.8%) occurred at segments or mid-block locations; 1,701 pedestrian crashes (22.2%) and 1,939 bicycle crashes (30.1%) occurred at non-signalized intersections; and 2,939 pedestrian crashes (38.4%) and 2,332 bicycle crashes (36.2%) occurred at signalized intersections. Figure 3.2 shows this distribution of pedestrian and bicycle crashes by location type.

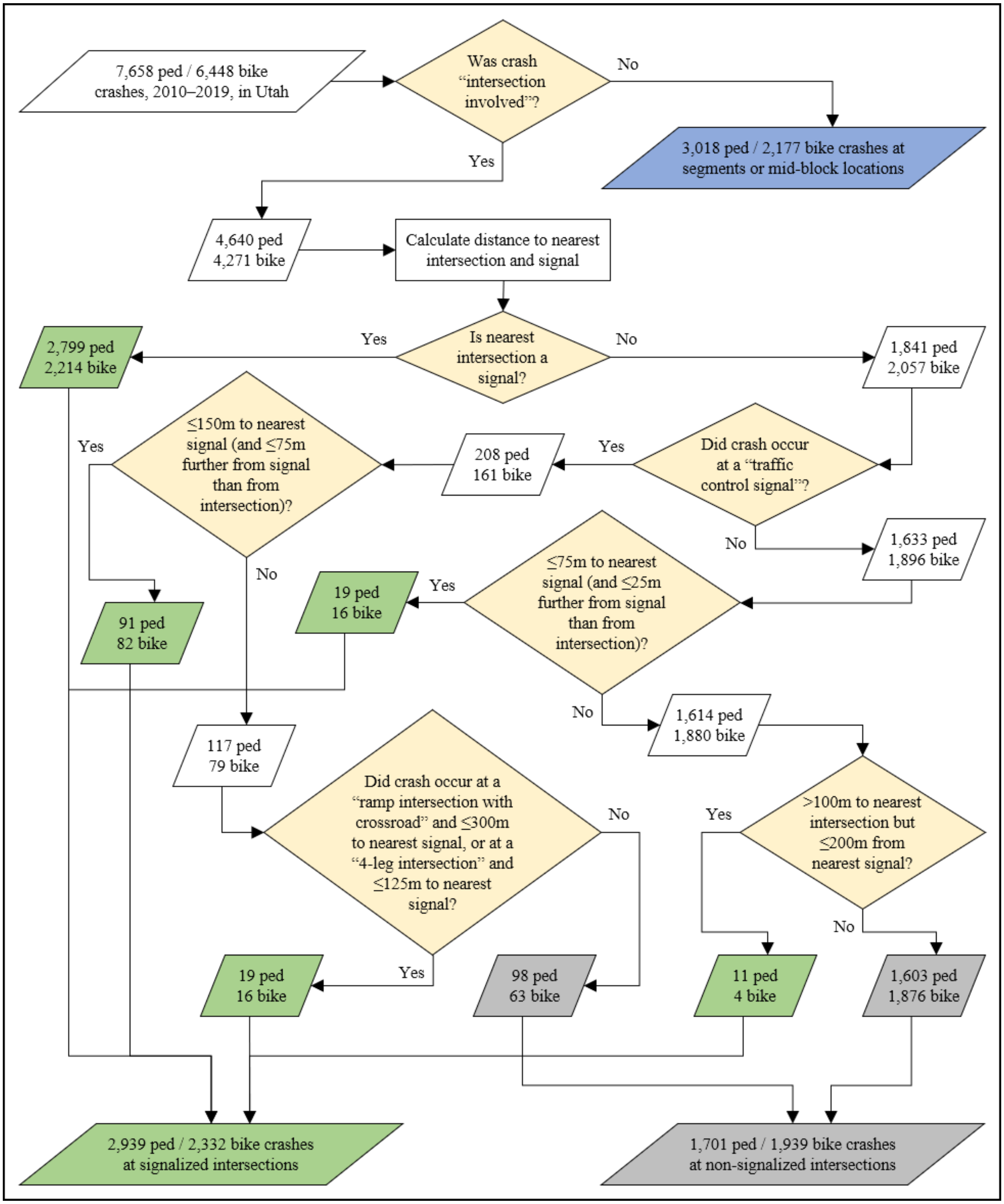

Figure 3.1 Flowchart Determining Pedestrian and Bicycle Crashes at Segments or Mid-Block Locations, Non-Signalized Intersections, and Signalized Intersections

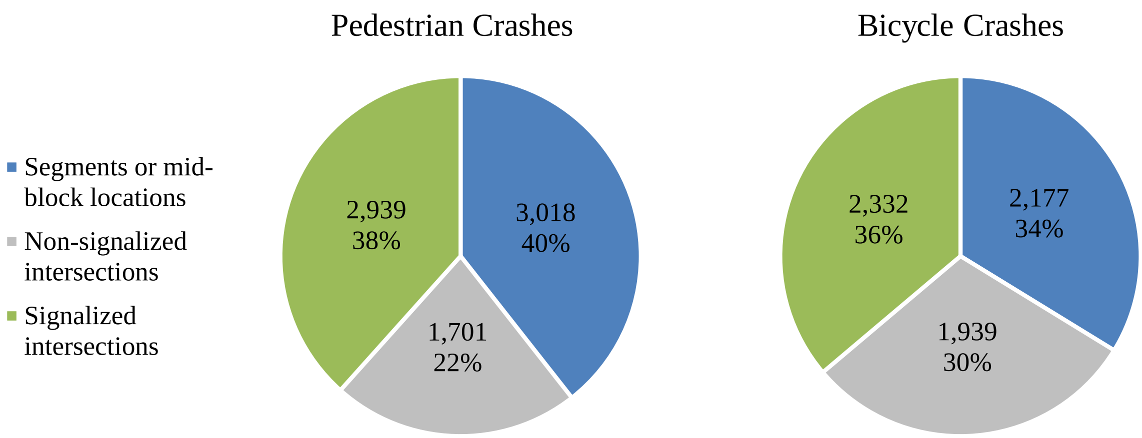

Figure 3.2 Pedestrian and Bicycle Crashes by Location

Table 3.1 shows the frequency of pedestrian and bicycle crashes by study location type, as well as the frequency and percentage of fatal and serious injury crashes. Overall, pedestrian crashes tend to have more severe outcomes than bicycle crashes: a greater share of pedestrian crashes (than bicycle crashes) involved a fatality or serious injury across all location types. Also, pedestrian and bicycle crashes on segments or mid-block locations tended to have more fatal and serious injury outcomes than crashes at intersections.

Table 3.1 Pedestrian and Bicycle Crashes by Location and Severity

		All crashes	*Fatal & serious injury*	
Location type	*Mode*	*Frequency*	*Frequency*	*Percentage*
Segments or mid-block locations	Pedestrian	3,018	787	26.08%
	Bicycle	2,177	245	11.25%
Non-signalized intersections	Pedestrian	1,701	263	15.46%
	Bicycle	1,939	180	9.28%
Signalized intersections	Pedestrian	2,939	400	13.61%
	Bicycle	2,332	175	7.50%

The following figures (Figure 3.3, Figure 3.4, Figure 3.5, Figure 3.6, Figure 3.7) show the distribution of pedestrian and bicycle crash frequencies across study locations. All crash frequency distributions were highly skewed. (Note the log-scale used for the number of locations.) In all cases, the majority of locations saw zero pedestrian or bicycle crashes over the ten-year study period. For segments, 94–97% of locations had zero crashes, while 97-99% of non-signalized intersections also saw zero crashes. For signalized intersections, around 50% had no pedestrian or bicycle crashes; although 85–93% had no fatal or serious injury crashes. Across all location types, the most pedestrian crashes experienced at one site was 23 (at a signalized intersection); the most bicycle crashes was 10 (at 4 signalized intersections). The most pedestrian or bicycle fatalities experienced at one site was 5 (pedestrian crashes at a signalized intersection).

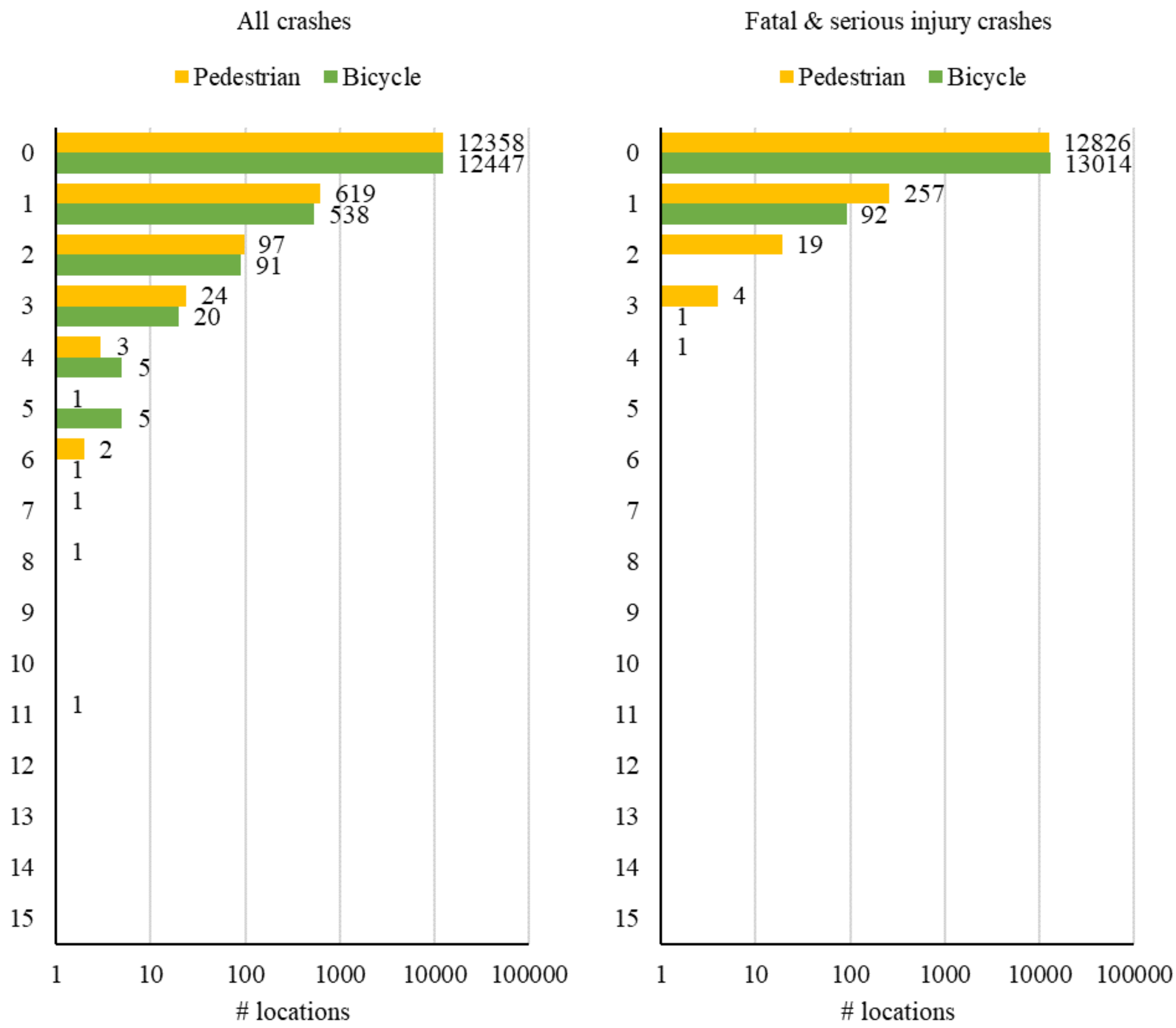

Figure 3.3 Crash Frequencies for State-Only Road Segments or Mid-Block Locations

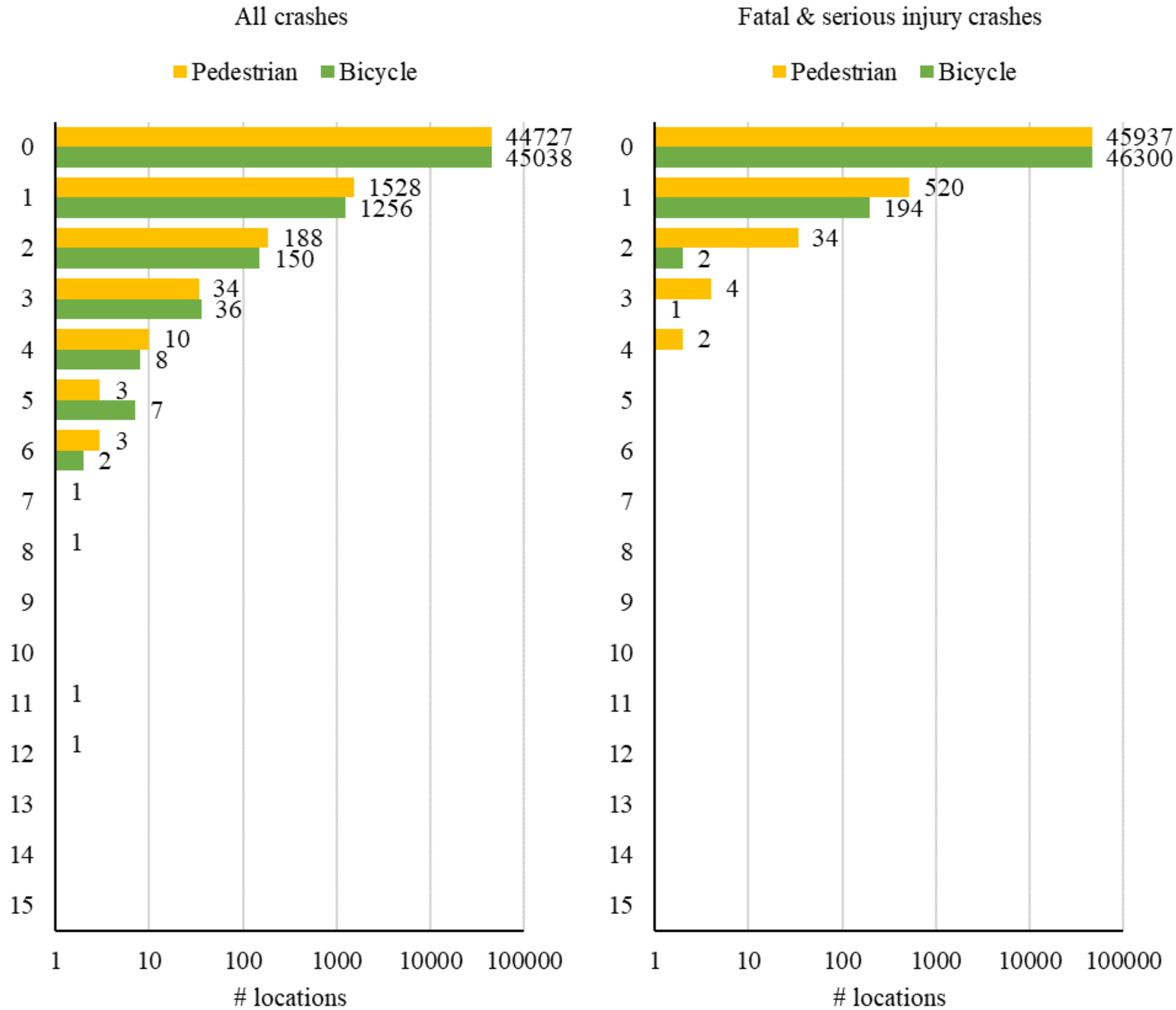

Figure 3.4 Crash Frequencies for State and Federal-Aid Road Segments or Mid-Block Locations

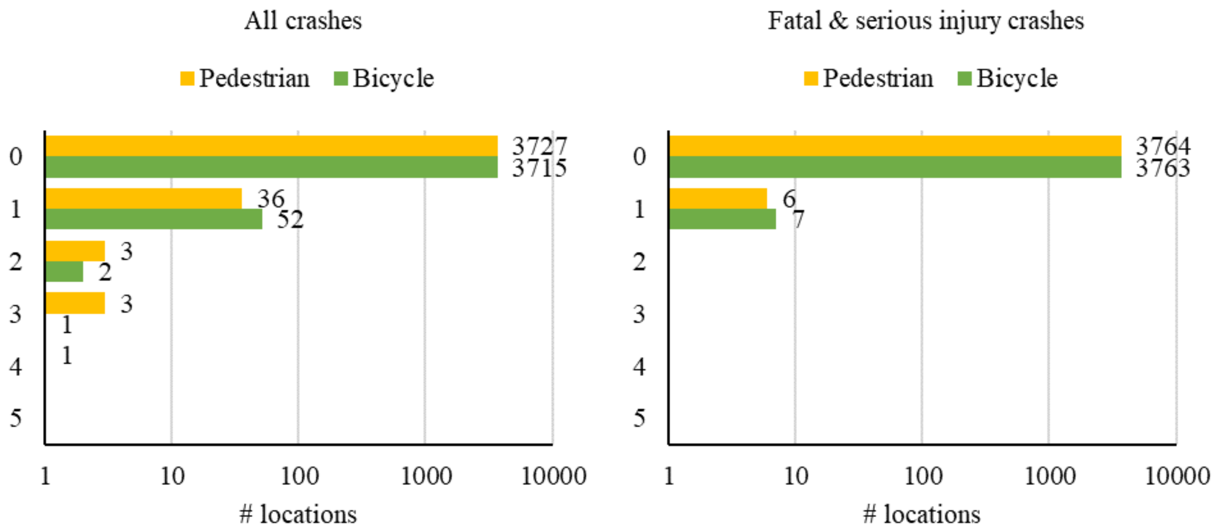

Figure 3.5 Crash Frequencies for Non-Signalized Intersections on State-Only Roads

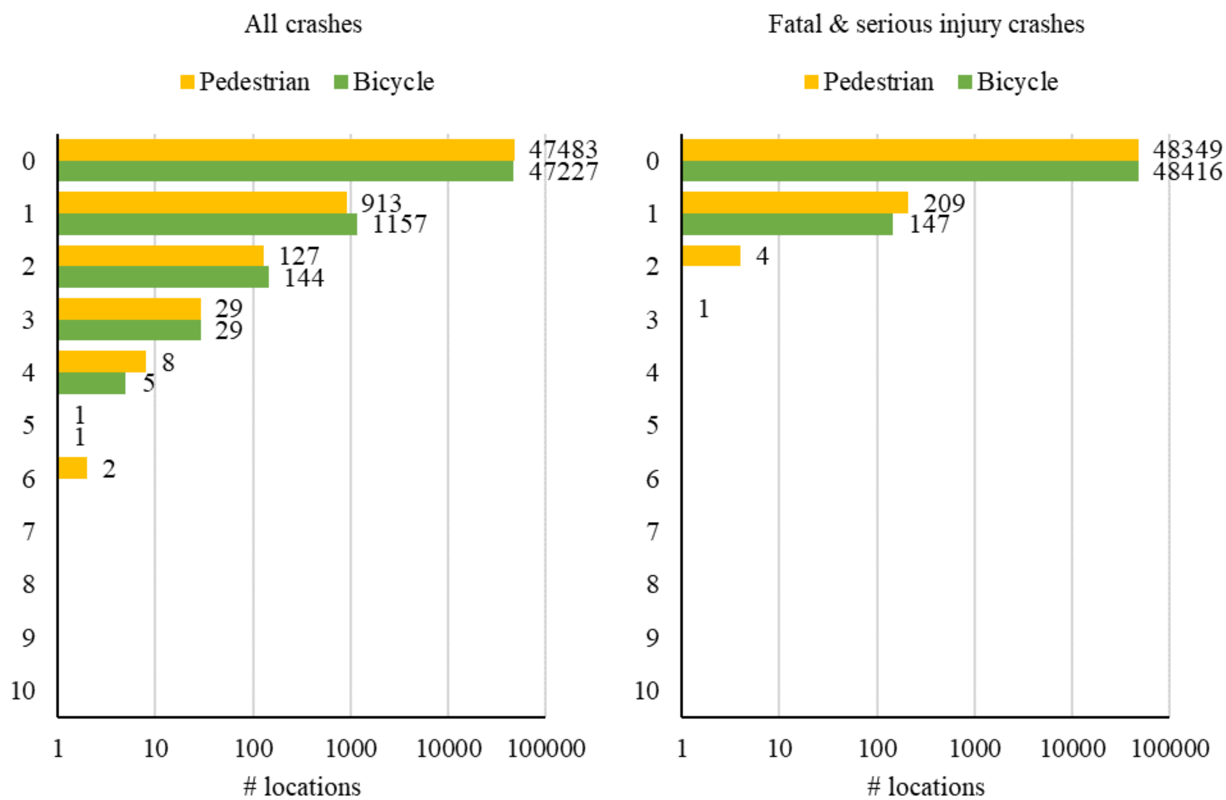

Figure 3.6 Crash Frequencies for Non-Signalized Intersections on State and Federal-Aid Roads

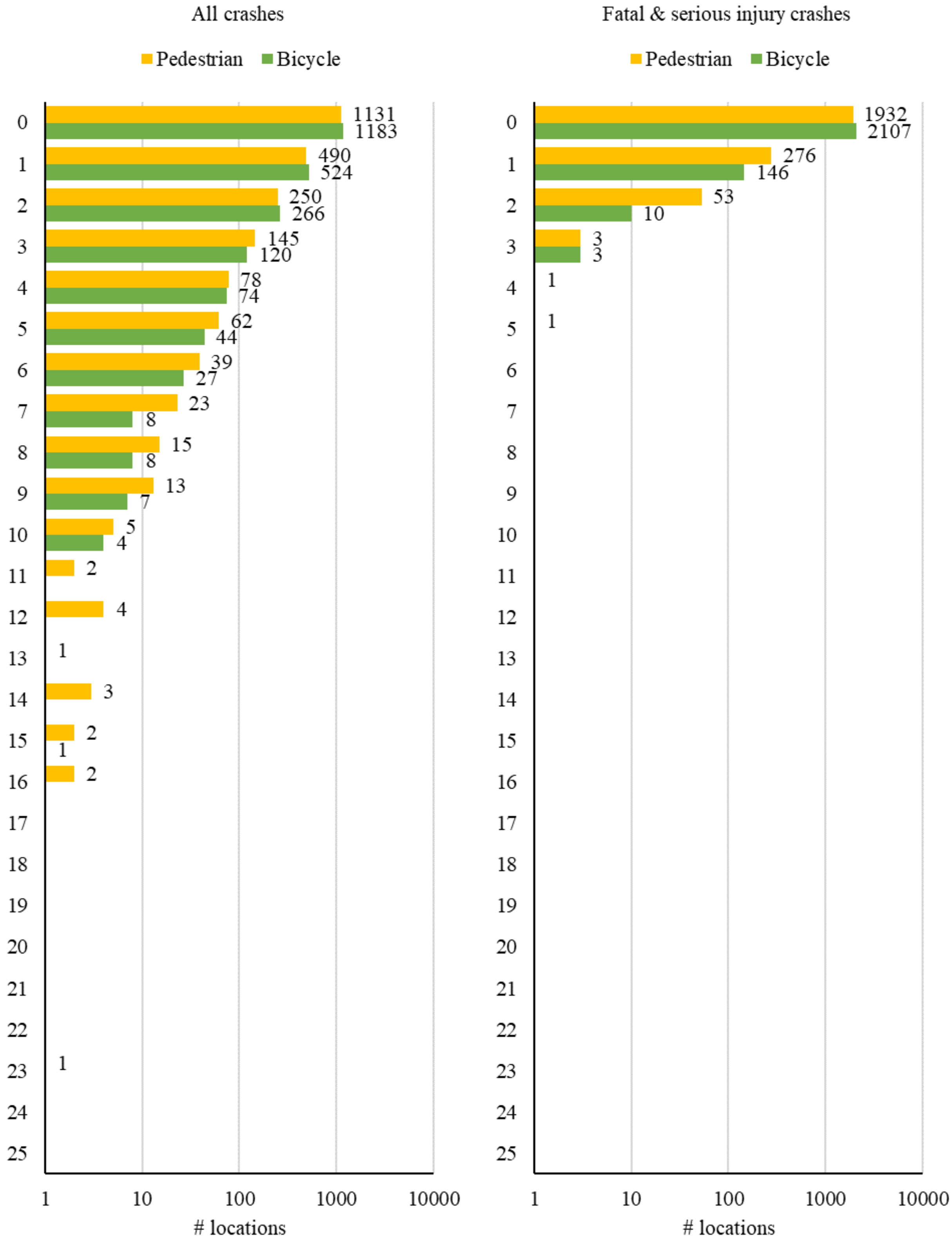

Figure 3.7 Crash Frequencies for Signalized Intersections

3.4 Exposure Data

Exposure is a critical concept in safety analysis; it attempts to measure the number of opportunities for an adverse safety outcome (such as a crash) to occur. Although exposure could be measured in different ways, one of the most common methods is to use the volume (or average count) of some type of traffic. Similarly, pedestrian and bicycle exposure are some of the key variables in crash frequency modeling. While motor vehicle traffic volumes are common ways to represent exposure in road networks, pedestrian and bicycle volume measurements can help to determine the levels of walking and bicycling activity on road segments and at intersections. However, sufficiently complete pedestrian and bicycle volume data are often unavailable due to the difficulty involved in collecting these sorts of exposure data.

This study has attempted to overcome this challenge by using two different data sources. Pedestrian exposure data were obtained through data (and various models built upon those data) originally collected from traffic signals. Bicycle exposure data were obtained through data from Strava Metro, a data platform built upon a popular fitness-tracking app. More details about these datasets are presented in the following subsections.

3.4.1 Pedestrian Exposure Data

One unique aspect and contribution of this study is the use of novel and more complete pedestrian exposure data than in previous work, which (as the literature review noted) is often missing from pedestrian safety studies. The pedestrian exposure data used here came from traffic signals, specifically derived from pedestrian activity events at signalized intersections that were recorded in high-resolution traffic signal controller logs (Sturdevant et al., 2012). When a traffic signal includes walk indications and pedestrian push-buttons for detection, two relevant events can be recorded. First, pedestrian detection events occur whenever the push-button is pressed, which could happen multiple times per signal cycle. Second, a pedestrian call registered event is recorded the first time in a cycle (usually) that a push-button is pressed for a particular phase or crossing. Either (or both) of these events may be used as a proxy for pedestrian crossing volumes, which is the typical measure of pedestrian exposure, within a given time period.

Although pedestrian traffic signal data are not perfect measures of pedestrian volumes (Blanc et al., 2015; Kothuri et al., 2017), recent work in an earlier UDOT research project by Singleton and colleagues (Singleton et al. 2020, Singleton & Runa, 2021) has demonstrated that such data can be used to predict pedestrian crossing volumes at signalized intersections with relative accuracy. Throughout 2019, more than 10,000 hours of videos of pedestrian crossing events were recorded at 90 signalized intersections throughout Utah, and more than 175,000 pedestrians were manually counted. These data were then compared to traffic signal push-button-based measures of pedestrian activity, using simple non-linear (quadratic and piece-wise linear) regression models predicting hourly pedestrian crossing volumes as a function of pedestrian signal activities. Over more than 22,500 hours of data, the correlation between observed and model-predicted hourly pedestrian crossing volumes was 0.84, with a mean absolute error of only 3.0 (Singleton et al., 2020; Singleton & Runa, 2021). Overall, that research project demonstrated that pedestrian signal data can be used to estimate reasonably accurate pedestrian crossing volumes. For the purposes of this research project, these pedestrian signal data provide greater temporal and spatial coverage for measuring pedestrian exposure (more locations over longer time periods), thus improving the understanding of relationships between pedestrian crashes and pedestrian volumes. For more information about these methods, see the research report (Singleton et al., 2020).

3.4.1.1 Exposure Data for Signalized Intersections

UDOT is a national leader in the development and deployment of the Automated Traffic Signal Performance Measures (ATSPM) system (Day et al., 2016) through which pedestrian events from high-resolution traffic signal controller logs can be obtained. As of Fall 2018, UDOT was centrally archiving data from more than 1,900 state and locally owned signals (Taylor and Mackey, 2018). For this study, one year (July 2017 through June 2018) of pedestrian data were obtained from all available traffic signals in Utah. After cleaning the data for missingness, the regression models developed by Singleton et al. (2020; Singleton & Runa, 2021) were applied to the pedestrian signal data. These estimates (by phase of the signal and hour of the year) were then aggregated across all crossings at each signal and all hours in each day, and then the daily estimates were averaged over all days in the year to calculate the annual average daily pedestrian (AADP) crossing volumes at each signal.

3.4.1.2 Exposure Data for Non-Signalized Intersections and Segments

Due to data and scale challenges with including pedestrians in regional travel-demand forecasting models (Singleton et al., 2018), planners interested in facility-specific information on walking activity levels have instead turned to using direct-demand models (Kuzmyak et al., 2014) which predict pedestrian volumes using observed counts and measures of the surrounding streetscape, land uses, built environment, and street network. Recent work by Singleton, Park, & Lee (2021) for a different UDOT research project has developed direct-demand models of annual average daily pedestrian volumes utilizing pedestrian traffic signal data and estimated crossing volumes from signalized intersections. Using the same data used as pedestrian exposure data for signalized intersections in this study (from nearly 1,500 signals), those authors estimated a model predicting AADP for signals as a function of surrounding characteristics: population and employment density, household size and income, vehicle ownership, residential and commercial land uses, intersection density and the percentage of four-way intersections, the number of schools, places of worship, and transit stops, park acreage, road classification, and traffic volumes. They then assembled information for the same built environment and neighborhood characteristics surrounding around 62,000 intersections in Utah, and applied the direct-demand models to estimate AADP crossing volumes at all intersections, including non-signalized intersections. For more information about these methods, see the research report (Singleton, Park, & Lee, 2021).

To obtain pedestrian exposure data for non-signalized intersections and for segments in this project, estimated pedestrian crossing volumes for all intersections from the model of Singleton, Park, and Lee (2021) were first obtained. Then, an iterative process was used to assign estimated pedestrian volumes to adjacent segments and junctions, using the following heuristic procedures. These procedures assume that: people make an average of one crossing per intersection (including people who cross two legs and those who turn a corner without crossing the street), people walk along a total of two legs (one from, one to) when passing through an intersection, and there are four legs at each intersection. Thus: # crossings ÷ (1 crossing / person) = # people at an intersection, and # people × (2 legs / person) × 4 legs = 50% × # crossings = # people on a segment.

- Step 1a: Transfer pedestrian volumes to segments from adjacent junctions.

- Step 1b: Calculate segment pedestrian volumes to be 50% of the average of pedestrian volumes from all adjacent junctions.
- Step 2a: Transfer pedestrian volumes to junctions from adjacent segments.
- Step 2b: Calculate junction pedestrian volumes to be 200% of the average of pedestrian volumes from all adjacent segments, or the originally estimated pedestrian volumes if available.
- Step 3: Repeat Steps 1 and 2 once more, and then repeat Step 1 again.

Due to limitations in the signal data as well as the data used to develop the built-environment regression models in Singleton, Park, and Lee (2021), estimated pedestrian volumes were only available for most intersections located in the six most populous Utah counties: Salt Lake, Utah, Davis, Weber, Washington, and Cache. Thus, pedestrian exposure data was only available for non-signalized intersections and segments in these counties. However, these counties comprise 84% of Utah's population and 92% of the bicycle and pedestrian crashes.

3.4.1.3 Summary of Pedestrian Exposure Data

The following figures (Figure 3.8, Figure 3.9, Figure 3.10, Figure 3.11, Figure 3.12) show the distribution of study locations for different ranges of pedestrian volumes. All distributions were positively skewed, with many locations having low pedestrian volumes and few locations having high pedestrian volumes. For segments or mid-block locations, pedestrian exposure ranged from almost 0 to nearly 725 (mean = 41, standard deviation = 52) pedestrians per day. For non-signalized intersections, pedestrian exposure ranged from almost 0 to nearly 1650 (mean = 72, standard deviation = 87) pedestrians per day. For signalized intersections, pedestrian exposure ranged from almost 0 to around 9250 (mean = 270, standard deviation = 573) pedestrians per day.

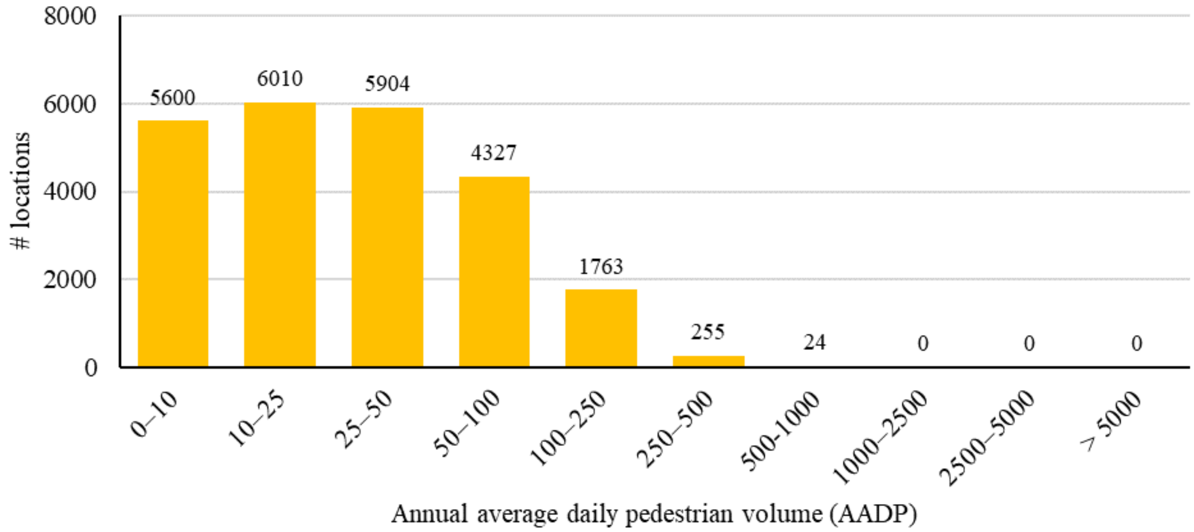

Figure 3.8 Pedestrian Volumes for State and Federal-Aid Road Segments or Mid-Block Locations

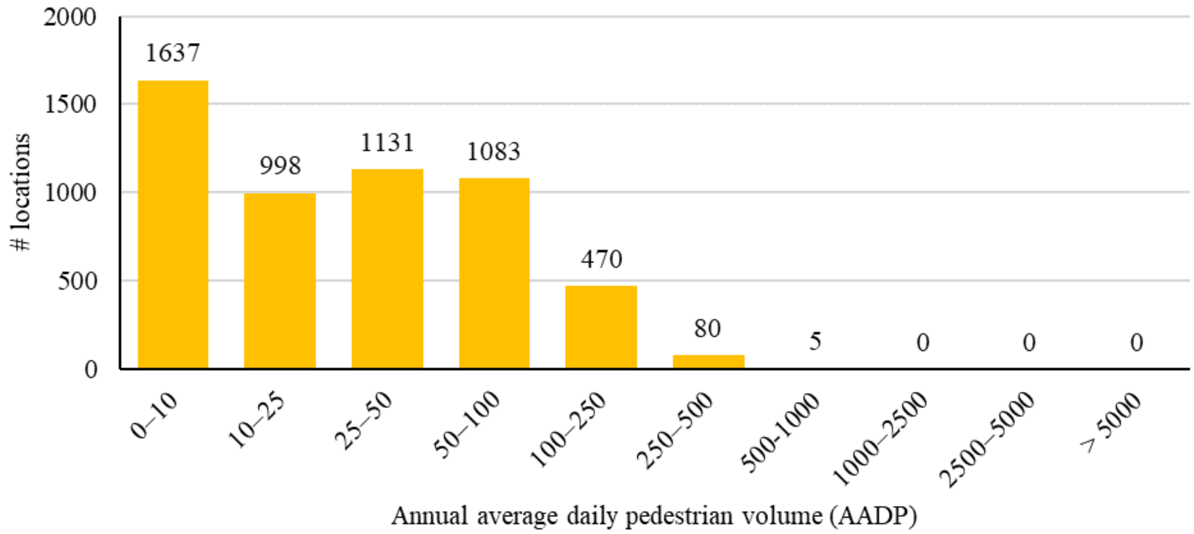

Figure 3.9 Pedestrian Volumes for State-Only Road Segments or Mid-Block Locations

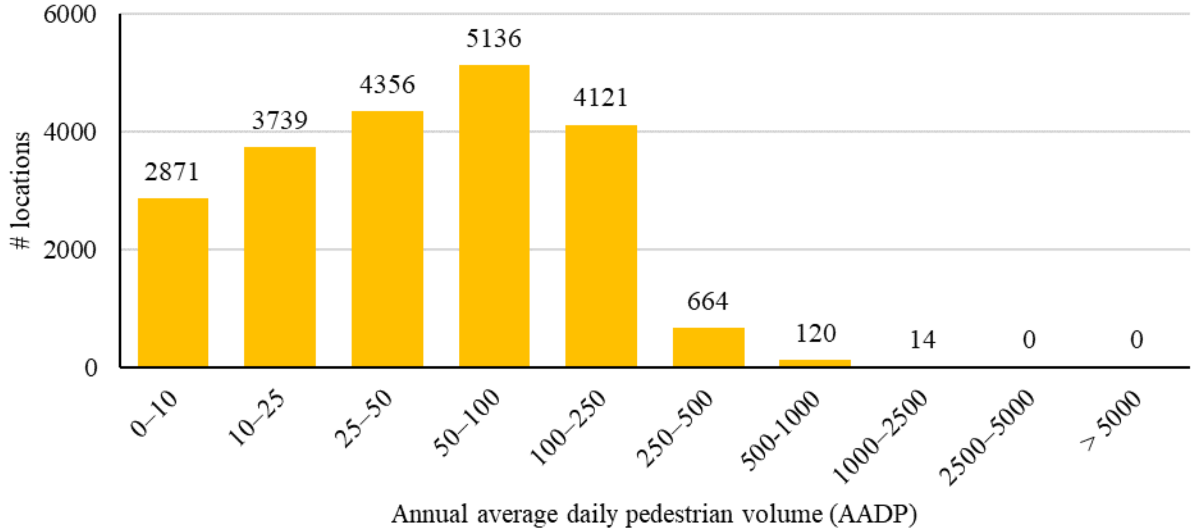

Figure 3.10 Pedestrian Volumes for Non-Signalized Intersections on State and Federal-Aid Roads

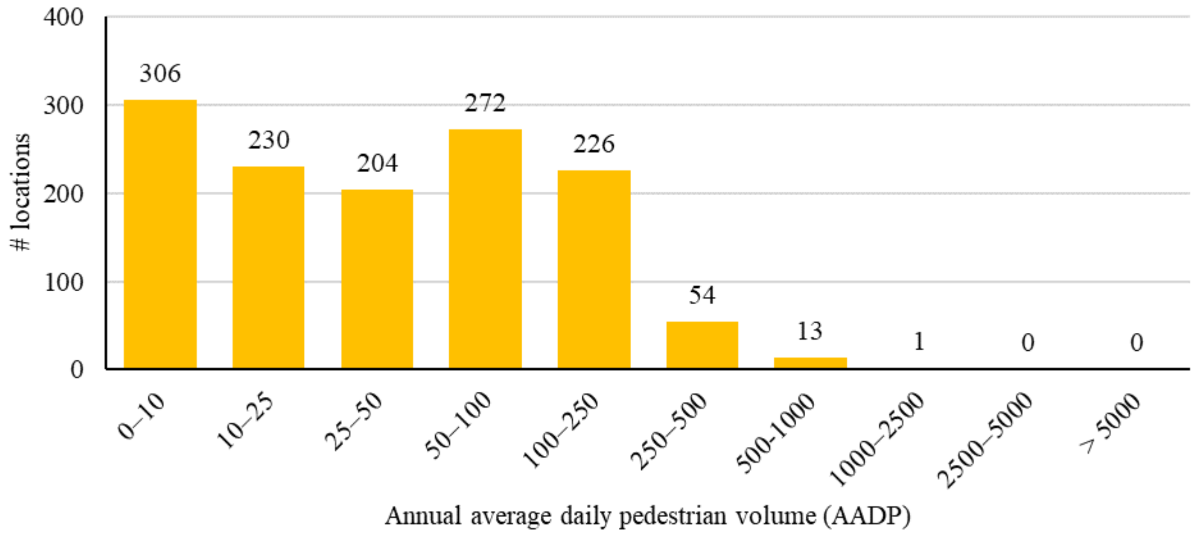

Figure 3.11 Pedestrian Volumes for Non-Signalized Intersections on State-Only Roads

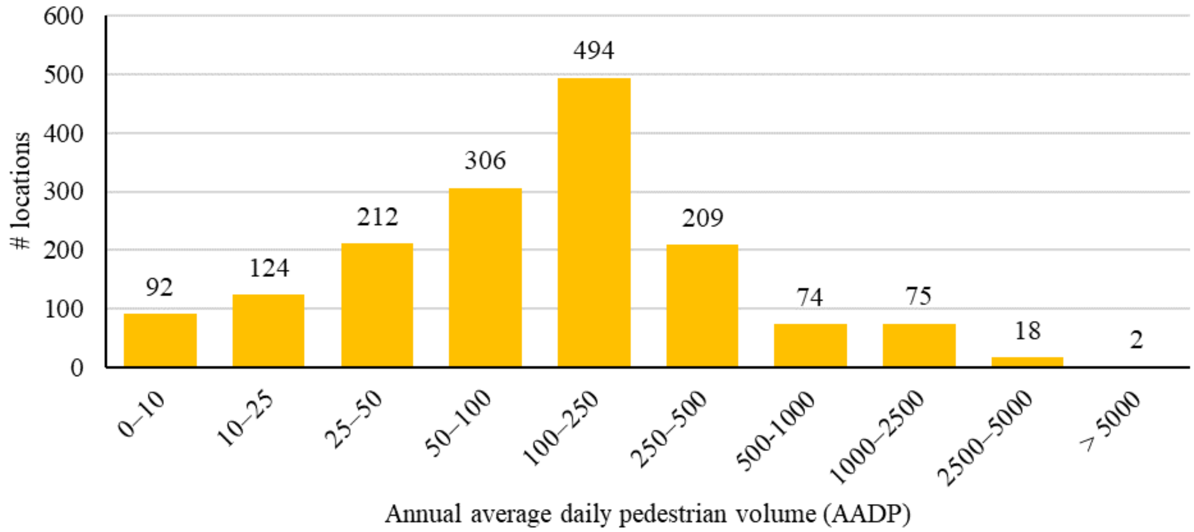

Figure 3.12 Pedestrian Volumes for Signalized Intersections

3.4.2 Bicycle Exposure Data

Bicycle volumes are similarly difficult to obtain as measures of bicycle exposure for crash data analysis. Thus, this project turned to crowdsourced data from Strava Metro as a proxy for bicycle volume. The Strava Metro dataset (Strava Metro, 2019) is a large collection of aggregated and de-identified bicycle trip information, obtained through users of the Strava fitness-tracking app. It is a recently developed source of trip data that is used by urban planners, engineers, and researchers to understand non-motorized mobility patterns. This recently emerged database has been used in transportation research—travel demand estimation (Roll, 2018), infrastructure evaluation (Skov-Petersen et al., 2017), and crash exposure (Sanders et al., 2017)—albeit in a limited manner. The data are collected from users' phone apps that help people keep track of their rides using GPS. The aggregated and de-identified dataset of bicycle counts in Utah for the year 2019 was used in this study. One important limitation of Strava bicycle data are that they are a small and potentially non-representative sample of all bicycle trips; specifically, they may overrepresent recreational bicycle trips. However, the share of bicycle trips recorded by Strava varies between regions and even within a region, so developing adjustment factors can be challenging and was beyond the scope of this project.

In order to make sure bicycle trip data were assigned to the road segment network accurately, the average daily trip information dataset and Strava's road network geodatabase were first joined together using common Edge IDs. On the next step, the joined spatial dataset and the segments derived from the links in the "Road Centerlines" geodatabase (see Section 3.2) were joined by attributes. This two-step process allowed the Strava spatial dataset and the segments/mid-block study locations to be inspected and filtered according to the common segment IDs. This network of road segment information now contained bicycle trip counts, and this broad network was filtered to identify state-only and state and federal-aid segments with bicycle trip information.

Strava data were available for intersections as well. The average daily bicycle trip information dataset and Strava's road node geodatabase were first joined together. On the next step, the joined spatial dataset and the intersections derived from the junctions in the "Street Network" geodatabase (see Section 3.2) were spatially joined to the nearest features. This two-step process was required because the datasets from the two different sources did not contain common identifiers. This network of intersections now contained bicycle trip counts, and this broad network was filtered to identify signalized intersections as well as non-signalized intersections on state-only and on state and federal-aid routes with bicycle trip information.

The following figures (Figure 3.13, Figure 3.14, Figure 3.15, Figure 3.16, Figure 3.17) show the distribution of study locations for different ranges of Strava bicycle volumes. All distributions were positively skewed, with many locations having low bicycles volumes and few locations having high bicycle volumes. For segments or mid-block locations, bicycle exposure ranged from almost 0 to nearly 82 (mean = 1.7, standard deviation = 3.7) bicyclists per day. For non-signalized intersections, bicycle exposure ranged from almost 0 to nearly 105 (mean = 1.6, standard deviation = 4.9) bicyclists per day. For signalized intersections, bicycle exposure ranged from almost 0 to around 94 (mean = 6.4, standard deviation = 7.9) bicyclists per day. Recall that these are certainly large underestimates of actual bicycle volumes, due to the use of a Strava-based sample.

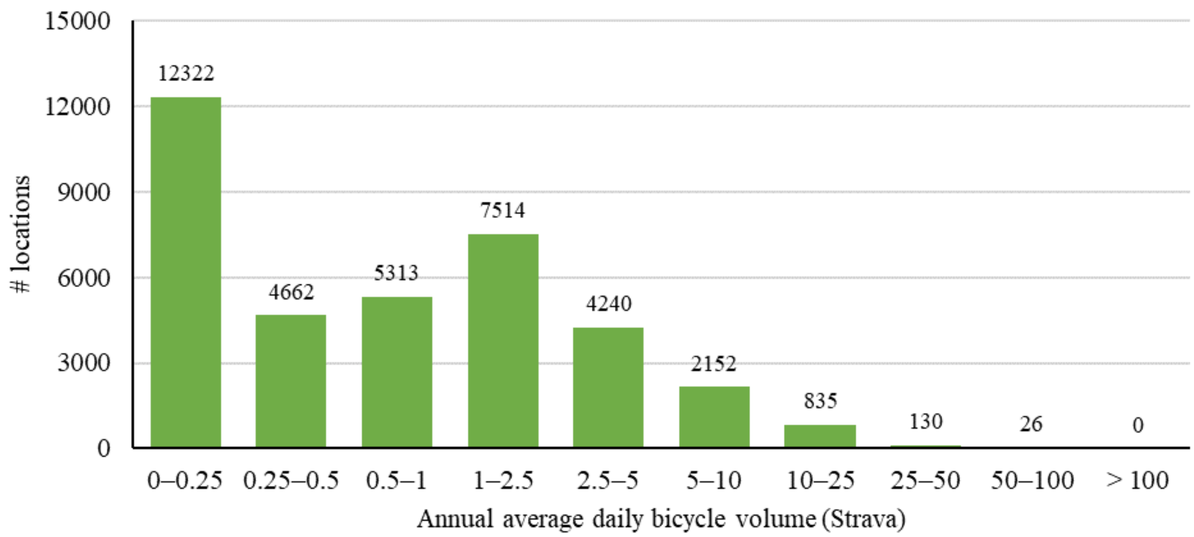

Figure 3.13 Bicycle Volumes for State and Federal-Aid Road Segments or Mid-Block Locations

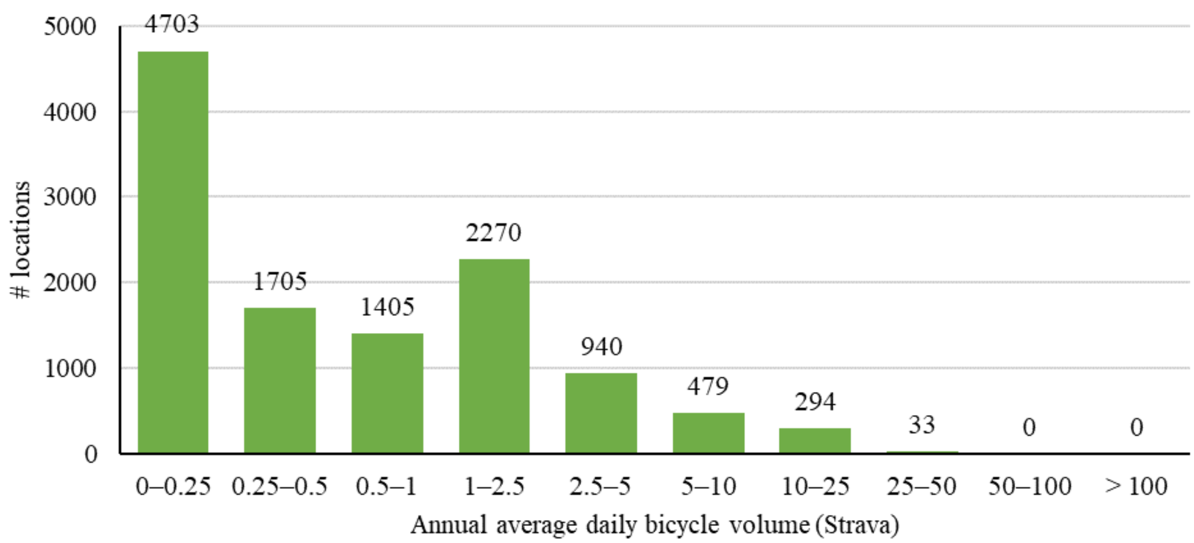

Figure 3.14 Bicycle Volumes for State-Only Road Segments or Mid-Block Locations

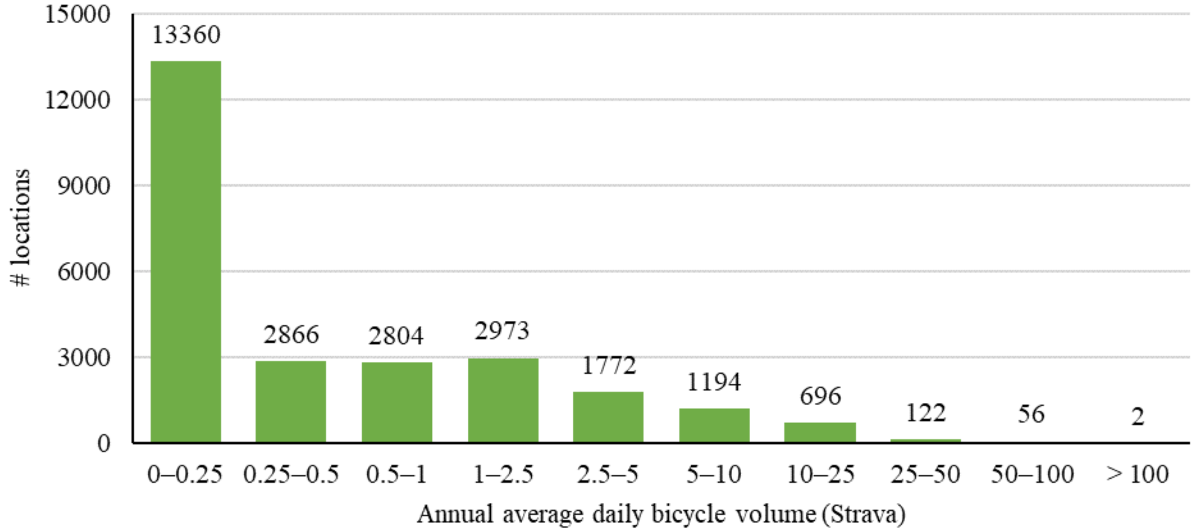

Figure 3.15 Bicycle Volumes for Non-Signalized Intersections on State and Federal-Aid Roads

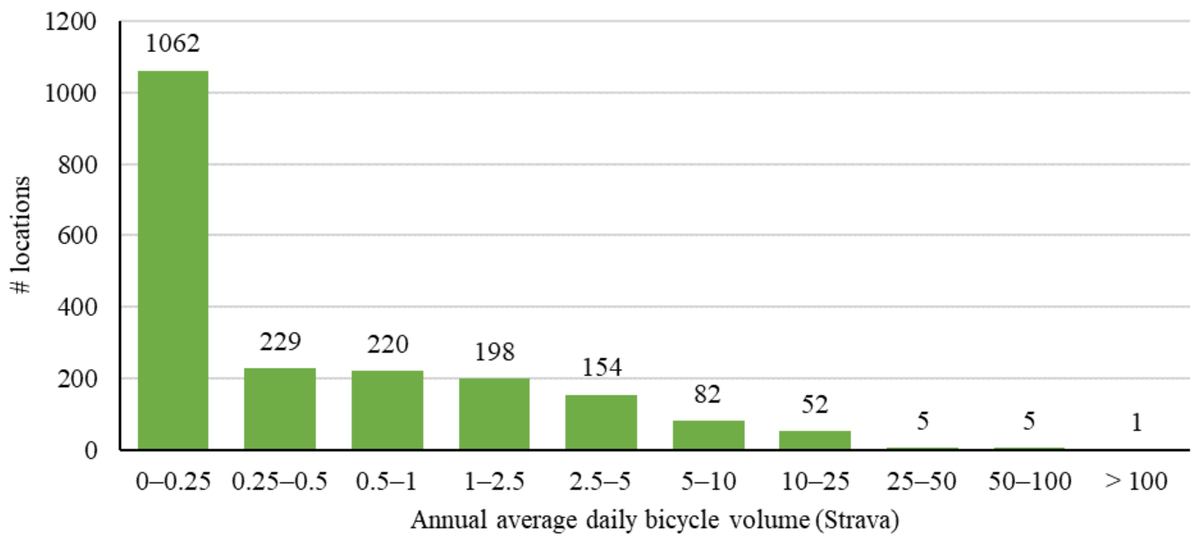

Figure 3.16 Bicycle Volumes for Non-Signalized Intersections on State-Only Roads

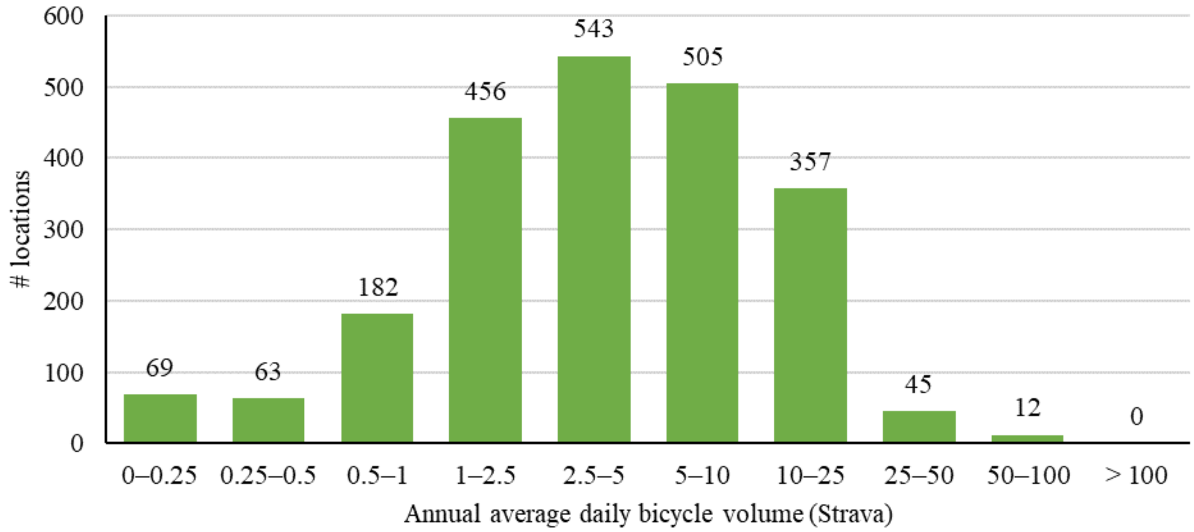

Figure 3.17 Bicycle Volumes for Signalized Intersections

3.5 Data about Roadway and Community Characteristics

In addition to data about crashes and exposure, other information about roadway and community characteristics were obtained. This information is needed for several reasons. First, this information helps to explain variations in crash frequencies across study locations, as independent variables in regression models. Second, characteristics that the models determine are significantly associated (either positively or negatively) with crash frequencies can indicate attributes or situations that are risk factors for pedestrian and bicycle crashes. Overall, this information may help to identify target locations and potential countermeasures for improving safety for people walking and bicycling.

Roadway and community characteristics were categorized into three groups: those related to roadway or intersection geometries, those related to traffic or transit volumes and operations, and those related to neighborhood land use, built environment, or sociodemographic characteristics. Each of these categories are described in more detail in the following subsections. Also, it is important to note that each characteristic (independent variable) may not apply to or be influential for a specific type of study location (segments, signalized and non-signalized intersections), and they may be measured differently for segments and for intersections. These details are also provided in the following subsections.

3.5.1 Data about Roadway Geometry and Traffic Characteristics

Most data about roadway geometry characteristics and roadway traffic characteristics were obtained as shapefiles from the UDOT Open Data Portal (UDOT, 2020) in Spring 2020. Geometry data included information about lanes, shoulders, traffic islands, medians, rumble strips, route grades, and barriers. Most of these roadway geometry characteristics were provided for all state highway segments, while barriers were only provided for locations where they existed. Traffic data included information about bus stops and transit stations, speed limits, driveways, motor vehicle traffic volumes (AADT), and truck volumes (percentages of AADT). Most of these roadway traffic characteristics were provided for state highway segments and some federal-aid highway segments, while transit stops/stations were provided as point locations.

All roadway geometry and traffic characteristics were first assigned to segment study locations using spatial and/or route matching, in order to generate characteristics for segments or mid-block locations. Then, most characteristics that were relevant for intersections—lanes, shoulders, traffic islands, medians, route grades, speed limits, motor vehicle traffic volumes (AADT), and truck volumes (percentages of AADT)—were assigned to adjacent junctions, in order to generate characteristics for non-signalized intersections. Other roadway traffic characteristics—bus stops and transit stations—were directly assigned to junctions using spatial matching. Some characteristics (distance to the nearest intersection and to the nearest signal) were directly created using spatial calculations only for non-signalized intersections.

As alluded to earlier, a major effort of this project involved merging different roadway data sources together and performing calculations in order to create combined datasets that could then be analyzed using statistical regression models. This section describes details of preparing and processing the roadway characteristics data prior to analysis. Separate subsections describe the process for segments or mid-block locations, non-signalized intersections, and signalized intersections.

3.5.1.1 Preparing Data for Segments or Mid-Block Locations

Most attributes for data about roadway characteristics were provided in spatial files with line features, and the lines may or may not have matched perfectly to the spatial line features used to define segments. For example, some segments were shorter than, longer than, or overlapping the relevant links from the roadway data files. Therefore, a spatial matching process was needed. In most cases, roadway shapefile lines were first buffered (usually using a 5 m buffer, although a 25 m buffer was used for barriers), and then segments were spatially joined with the buffered roadway lines, only links with the same route number as the segment were retained, and relevant attributes were transferred over to segments.

In some cases, there were multiple matches of roadway characteristics to segments, such as in the case when a segment overlapped with two roadway shapefile lines, leading to multiple values for each attribute. In these situations, a data consolidation process was needed to obtain one value for each attribute. Depending on the attribute, one of four functions was applied to consolidate multiple values into one value:

- *Longest distance*: Attributes were tabulated according to their unique values, and the total link lengths of each attribute value were calculated. The value present for the longest total distance was retained. This was the most common function applied, especially for categorical or integer attributes (such as the number of through lanes or the island type).
- *Distance-weighted average*: The attribute values were multiplied by the link lengths and divided by the total lengths, yielding a distance-weighted average attribute value. This was commonly applied to continuous numeric attributes that measured widths or heights (such as shoulder width).
- *Maximum*: The largest value among all values was retained. This was used only for a few categorical or integer attributes where the maximum was more relevant (such as number of left turn or right-turn lanes).
- *Sum*: The sum of all values was used. This was used only for continuous numeric attributes that measured lengths (such as barrier length).

3.5.1.2 Preparing Data for Non-Signalized Intersections

Most attributes for data about roadway characteristics were provided in spatial files with line features, not point features. Therefore, most attributes for non-signalized intersections had to be transferred over and derived from attributes for the adjacent segments. (See Section 3.2 for details on how junctions and segments were matched.) Since most intersections had at least three adjacent segments, leading to multiple values for each attribute, a data consolidation process was needed to obtain one value for each attribute. Depending on the attribute, one of four functions was applied to consolidate multiple values into one value:

- *Mean*: The arithmetic mean (or average) of all attribute values was calculated, and this single value was retained. This was used for most attributes, including integer and continuous numeric attributes like counts and widths.
- *Maximum*: The largest value among all values was retained. This was used only for a few categorical or integer attributes where the maximum was more relevant.

3.5.1.3 Preparing Data for Signalized Intersections

In comparison, intersection geometry and traffic characteristics for signalized intersections were collected as part of a different UDOT research project (Singleton, Mekker, & Islam, 2021) using both similar and different approaches. Many characteristics were captured from satellite and street-level imagery, including: intersection type (the number of legs), crossing distance, crosswalk marking type (standard vs. continental vs. ladder/zebra), channelized right turns, prohibited right turns on red, and the presence of bike lanes and street lights. Motor vehicle traffic volumes (AADT) were assigned using the same process as for non-signalized intersections. More detailed information about the data collection process for signalized intersections can be found elsewhere (Singleton, Mekker, & Islam, 2021).

3.5.2 Data about Neighborhood Community Characteristics

Most data about neighborhood community characteristics were taken from U.S. Census data, obtained through the EPA's Smart Location Database (SLD) version 2.0 (EPA, 2013). The SLD contains dozens of attributes about housing density, land-use diversity, neighborhood design, destination accessibility, transit service, employment, and demographics, all measured for almost every Census block group in the country. Most data in the 2013 SLD were obtained or calculated from the 2010 decennial Census, the 2010 five-year American Community Survey (ACS), or the 2010 Longitudinal Employer Household Dynamics (LEHD) dataset. At the time of this study, this was the most up-to-date version of the SLD available.

For both segments and non-signalized intersections, the following information was calculated from SLD variables: population density, employment density, percentage of zero-vehicle households, average jobs per household, average household income, percentage of population with a disability, and percentage of the population of non-White or Hispanic race/ethnicity. This information was calculated as the area-weighted average of values for all Census block groups intersecting a circular buffer of 400 m around each segment or non-signalized intersection.

For signalized intersections, a slightly different process was followed. Data on land uses, the built environment, and neighborhood sociodemographic characteristics were obtained from various sources, including the UGRC website, the 2017 five-year, or the 2017 LEHD dataset, at the Census block level when possible. Values for signalized intersections were calculated in a similar way as for segments and non-signalized intersections, except using a street network-based buffer of 0.25 mi around each signal. More information about the data collection process for signalized intersections can be found elsewhere (Singleton, Mekker, & Islam, 2021; Singleton, Park, & Lee, 2021).

3.6 Descriptive Statistics

<u>3.6.1 Segments or Mid-Block Locations</u>

Descriptive statistics of the combined datasets for non-signalized intersections are shown in Table 3.2 for state-only road segments or mid-block locations and Table 3.3 for state and federal-aid road segments or mid-block locations. The state and federal-aid dataset contains more locations (up to 46,497 vs. 13,107), but the state-only dataset contains more variables, because several roadway geometry and traffic characteristics were only available for locations on state highways.

Table 3.2 Descriptive Statistics for State-Only Road Segments or Mid-Block Locations

Variable	*N*	*Min.*	*Max.*	*Mean*	*Std. Dev.*
Dependent variable: Crash frequency					
# pedestrian-involved crashes	13107	0.00	11.00	0.0717	0.3422
# bicycle-involved crashes	13107	0.00	6.00	0.0634	0.3113
# fatal or serious injury pedestrian-involved crashes	13107	0.00	4.00	0.0237	0.1697
# fatal or serious injury bicycle-involved crashes	13107	0.00	3.00	0.0072	0.0875
Measures of exposure					
Annual average daily pedestrian volume (AADP)	5404	0.17	616.36	43.5195	57.0362
Annual average daily bicycle volume (Strava)	12204	0.00	42.81	1.4381	3.0833
Annual average daily traffic (AADT)	12839	30.00	129000.	10659.01	12936.93
Roadway geometry and traffic characteristics					
Truck proportion of AADT	12838	0.01	0.85	0.2422	0.1207
Interstate, US, or Utah numbered highway	13107	0.00	1.00	0.9898	0.1006
One-way road segment	13107	0.00	1.00	0.0258	0.1585
Elevated road segment	13107	0.00	1.00	0.0193	0.1376
Through lane width (ft)	12769	0.00	32.00	11.9613	1.2694
# through lanes	12769	0.00	8.00	2.8044	1.2628
# left-turn lanes	12769	0.00	4.00	0.6022	0.9265
# right-turn lanes	12769	0.00	3.00	0.3751	0.6562
# two-way left-turn lanes	12769	0.00	1.00	0.1926	0.3943
Presence of a right shoulder	12769	0.00	1.00	0.8806	0.3242
Presence of an island	13107	0.00	1.00	0.0992	0.2989
Presence of a median	12686	0.00	1.00	0.1002	0.3003
Presence of rumble strips	12899	0.00	1.00	0.2329	0.4227
Presence of a right barrier	13107	0.00	1.00	0.1327	0.3392
Driveways (# / km), commercial	13107	0.00	97.46	4.5263	11.1670
Driveways (# / km), industrial	13107	0.00	95.99	1.1337	3.7613
Driveways (# / km), residential	13107	0.00	117.65	6.0989	13.3337
# bike lanes	12769	0.00	2.00	0.0935	0.4092
Percentage grade	12762	0.00	12.73	1.5126	1.5486
Speed limit (mi / hr)	13107	0.00	65.00	48.9902	13.2925
# bus stops	13107	0.00	8.00	0.1570	0.5164
# commuter rail stations (within 400 m)	13107	0.00	1.00	0.0021	0.0453
# light rail stations (within 400 m)	13107	0.00	3.00	0.0161	0.1481
Neighborhood community characteristics [a]					
Residential density (housing units / acre)	13107	0.00	12.39	0.6086	1.1205
Employment density (jobs / acre)	13107	0.00	39.58	1.2431	3.5112
Jobs-housing balance (jobs / household)	13107	0.00	18935.	11.6529	350.1436
Household income (median, $1,000)	12110	15.71	177.75	62.6163	20.7199
% zero-vehicle households	13107	0.00	38.21	3.3643	4.5223
% population with a disability	13032	0.00	80.97	30.1898	8.9411
% population of Hispanic or non-white race/ethnicity	13032	0.00	100.00	11.0107	14.3426

[a] These variables were measured using an area-weighted average of all Census block groups within 400 m.

Table 3.3 Descriptive Statistics for State and Federal-Aid Road Segments or Mid-Block Locations

Variable	*N*	*Min.*	*Max.*	*Mean*	*Std. Dev.*
Dependent variable: Crash frequency					
# pedestrian-involved crashes	46497	0.00	12.00	0.0455	0.2628
# bicycle-involved crashes	46497	0.00	6.00	0.0375	0.2314
# fatal or serious injury pedestrian-involved crashes	46497	0.00	4.00	0.0131	0.1241
# fatal or serious injury bicycle-involved crashes	46497	0.00	3.00	0.0043	0.0672
Measures of exposure					
Annual average daily pedestrian volume (AADP)	23883	0.16	720.86	41.2490	51.7306
Annual average daily bicycle volume (Strava)	39356	0.00	81.84	1.6911	3.7126
Annual average daily traffic (AADT)	36338	0.00	300000.	8638.20	15918.24
Roadway geometry and traffic characteristics					
Interstate, US, or Utah numbered highway	46497	0.00	1.00	0.3631	0.4809
One-way road segment	46497	0.00	1.00	0.0918	0.2888
Elevated road segment	46497	0.00	1.00	0.0249	0.1560
Speed limit (mi / hr)	46497	0.00	75.00	39.2276	14.2699
# bus stops	46497	0.00	8.00	0.1178	0.4484
# commuter rail stations (within 400 m)	46497	0.00	1.00	0.0040	0.0635
# light rail stations (within 400 m)	46497	0.00	4.00	0.0169	0.1520
Neighborhood community characteristics [a]					
Residential density (housing units / acre)	46497	0.00	12.58	0.9020	1.3816
Employment density (jobs / acre)	46497	0.00	39.58	1.4620	3.5119
Jobs-housing balance (jobs / household)	46497	0.00	18935.	48.4563	799.1602
Household income (median, $1,000)	43669	15.71	186.36	66.2525	23.4077
% zero-vehicle households	46497	0.00	38.21	3.3662	4.3862
% population with a disability	46197	0.00	100.00	30.1834	8.6548
% population of Hispanic or non-white race/ethnicity	46197	0.00	100.00	11.4049	13.9926

[a] These variables were measured using an area-weighted average of all Census block groups within 400 m.

3.6.2 Non-Signalized Intersections

Descriptive statistics of the combined datasets for non-signalized intersections are shown in Table 3.4 for intersection on state roads only and Table 3.5 for intersections on state and federal-aid roads. The state and federal-aid dataset contains more locations (up to 48,563 vs. 3,770), but the state-only dataset contains more variables, because several roadway geometry and traffic characteristics were only available for locations on state highways.

Table 3.4 Descriptive Statistics for Non-Signalized Intersections on State-Only Roads

Variable	*N*	*Min.*	*Max.*	*Mean*	*Std. Dev.*
Dependent variable: Crash frequency					
# pedestrian-involved crashes	3770	0.00	4.00	0.0146	0.1547
# bicycle-involved crashes	3770	0.00	3.00	0.0156	0.1344
# fatal or serious injury pedestrian-involved crashes	3770	0.00	1.00	0.0016	0.0399
# fatal or serious injury bicycle-involved crashes	3770	0.00	1.00	0.0019	0.0431
Measures of exposure					
Annual average daily pedestrian volume (AADP)	1306	0.36	1056.62	69.6877	99.3037
Annual average daily bicycle volume (Strava)	2008	0.01	103.68	1.6076	5.3731
Average daily traffic, major direction ($AADT_{MAJ}$)	3359	30.00	287500.	11569.13	19764.90
Roadway geometry and traffic characteristics					
Truck proportion of $AADT_{MAJ}$	3350	0.03	0.85	0.2532	0.1222
# intersection legs or approaches	3770	1.00	7.00	2.5095	0.7454
Through lane width (ft), major direction	3391	9.00	29.50	12.0232	1.1162
# through lanes, major direction	3391	1.00	8.00	2.6732	1.1563
# left-turn lanes, major direction	3391	0.00	4.00	0.5122	0.8290
# right-turn lanes, major direction	3391	0.00	2.50	0.3182	0.5262
Shoulder width (ft), major direction	3388	0.00	19.19	4.9126	3.1586
Median width (ft), major direction	3354	0.00	504.27	13.7138	41.2281
Presence of a bike lane	3770	0.00	1.00	0.0366	0.1878
Percentage grade (maximum of legs)	3393	0.00	12.73	1.9862	1.7449
Speed limit (mi / hr) (maximum of legs)	3770	10.00	75.00	51.3912	14.0723
Distance (km) to nearest intersection	3770	0.00	24.28	0.3591	0.7920
Distance (km) to nearest signal	3770	0.00	157.46	14.3354	21.7876
# bus stops	3770	0.00	4.00	0.0286	0.2066
# commuter rail stations (within 400 m)	3770	0.00	1.00	0.0029	0.0539
# light rail stations (within 400 m)	3770	0.00	3.00	0.0093	0.1039
Neighborhood community characteristics [a]					
Residential density (housing units / acre)	3770	0.00	8.28	0.4394	0.8824
Employment density (jobs / acre)	3770	0.00	37.33	1.0385	2.9153
Jobs-housing balance (jobs / household)	3770	0.00	18935.	63.4091	961.5402
Household income (median, $1,000)	3544	15.71	179.17	64.7344	21.8746
% zero-vehicle households	3770	0.00	38.21	2.6213	3.5835
% population with a disability	3710	0.00	80.97	30.6903	8.2540
% population of Hispanic or non-white race/ethnicity	3710	0.00	100.00	9.8749	12.8753

[a] These variables were measured using an area-weighted average of all Census block groups within 400 m.

Table 3.5 Descriptive Statistics for Non-Signalized Intersections on State and Federal-Aid Roads

Variable	*N*	*Min.*	*Max.*	*Mean*	*Std. Dev.*
Dependent variable: Crash frequency					
# pedestrian-involved crashes	48563	0.00	6.00	0.0268	0.1963
# bicycle-involved crashes	48563	0.00	5.00	0.0321	0.2054
# fatal or serious injury pedestrian-involved crashes	48563	0.00	3.00	0.0045	0.0693
# fatal or serious injury bicycle-involved crashes	48563	0.00	1.00	0.0030	0.0549
Measures of exposure					
Annual average daily pedestrian volume (AADP)	21021	0.32	1634.56	72.3830	87.4576
Annual average daily bicycle volume (Strava)	25845	0.01	104.70	1.6315	4.8510
Average daily traffic, major direction ($AADT_{MAJ}$)	37994	0.00	300000.	7500.83	15492.85
Roadway geometry and traffic characteristics					
# intersection legs or approaches	48563	1.00	7.00	2.8733	0.6696
Presence of a bike lane	48525	0.00	1.00	0.0645	0.2456
Speed limit (mi / hr) (maximum of legs)	48563	0.00	75.00	41.0795	15.0966
Distance (km) to nearest intersection	48563	0.00	24.33	0.2796	0.5570
Distance (km) to nearest signal	48563	0.00	157.46	15.7713	25.4589
# bus stops	48563	0.00	5.00	0.0629	0.3041
# commuter rail stations (within 400 m)	48563	0.00	1.00	0.0021	0.0453
# light rail stations (within 400 m)	48563	0.00	3.00	0.0082	0.1009
Neighborhood community characteristics [a]					
Residential density (housing units / acre)	48563	0.00	13.04	0.7529	1.2838
Employment density (jobs / acre)	48563	0.00	39.58	1.0731	2.7047
Jobs-housing balance (jobs / household)	48563	0.00	18935.	37.4513	734.5206
Household income (median, $1,000)	45874	15.71	186.36	65.2081	22.9199
% zero-vehicle households	48563	0.00	38.21	3.0516	3.8937
% population with a disability	48346	0.00	100.00	30.1549	8.6293
% population of Hispanic or non-white race/ethnicity	48346	0.00	100.00	10.8387	14.0620

[a] These variables were measured using an area-weighted average of all Census block groups within 400 m.

3.6.3 Signalized Intersections

Descriptive statistics of the combined dataset for signalized intersections are shown in Table 3.6. Up to 2,266 locations are available, but fewer locations are available with minor-street traffic volumes, because these were usually only available for signalized intersections on state roads.

Table 3.6 Descriptive Statistics for Signalized Intersections

Variable	***N***	***Min.***	***Max.***	***Mean***	***Std. Dev.***
Dependent variable: Crash frequency					
# pedestrian-involved crashes	2266	0.00	23.00	1.2970	2.0897
# bicycle-involved crashes	2266	0.00	15.00	1.0291	1.5752
# fatal or serious injury pedestrian-involved crashes	2266	0.00	5.00	0.1765	0.4629
# fatal or serious injury bicycle-involved crashes	2266	0.00	3.00	0.0772	0.2968
Measures of exposure					
Annual average daily pedestrian volume (AADP)	1606	0.16	9255.95	269.9476	572.7814
Annual average daily bicycle volume (Strava)	2232	0.01	94.44	6.3698	7.9256
Average daily traffic, major direction ($AADT_{MAJ}$)	2131	10.00	186000.	21474.27	12607.07
Average daily traffic, minor direction ($AADT_{MIN}$)	1599	0.00	57000.	7027.63	7536.85
Transportation characteristics					
Intersection type					
2-leg (mid-block)	2266	0.00	1.00	0.0508	0.2195
3-leg	2266	0.00	1.00	0.1337	0.3404
4-leg	2266	0.00	1.00	0.7913	0.4065
Other: 5-leg, DDI, SPUI	2266	0.00	1.00	0.0229	0.1498
# crosswalks, total	2266	0.00	4.00	3.0949	1.2734
# approaches with no pedestrian crossing	2266	0.00	4.00	0.6695	1.1101
# crosswalks, standard markings	2266	0.00	4.00	2.7180	1.4661
# crosswalks, continental/ladder/zebra markings	2266	0.00	4.00	0.3411	0.7724
Crosswalk length (mean, ft)	2119	0.00	185.00	79.0196	20.0409
# approaches with no right-turn-on-red	2266	0.00	2.00	0.0132	0.1181
# approaches with channelized right turns	2266	0.00	4.00	0.1893	0.6637
# approaches with bike lanes	2266	0.00	4.00	0.5993	1.0447
# of bus stops within 300 ft of intersection	2266	0.00	6.00	0.8274	1.1369
# approaches with near-side bus stops	2266	0.00	4.00	0.2807	0.5752
Absence of overhead street lighting	2263	0.00	1.00	0.0658	0.2481
Land use and built environment characteristics [a]					
% land use, residential	1959	0.00	84.00	30.9985	23.7204
% land use, commercial	1959	0.00	91.75	28.0318	20.9235
% land use, industrial	1959	0.00	82.92	2.8128	10.4120
% land use, vacant	1959	0.00	100.00	5.4565	11.2332
Population density (1,000 people / mi^2)	1958	0.02	23.44	4.4928	3.0092
Employment density (1,000 jobs / mi^2)	1952	0.02	216.03	7.6636	12.9044
Park area (acre)	1959	0.00	37.16	1.4805	3.6356
# schools	1959	0.00	5.00	0.2797	0.5914
# places of worship	1959	0.00	6.00	0.4773	0.7772
Sociodemographic characteristics [a]					
Household income (median, $1,000)	1957	15.71	144.61	62.7768	22.5974
Vehicle ownership (mean)	1936	0.39	2.99	1.7285	0.4520
Household size (mean)	1958	1.39	13.72	3.1404	0.8645
% population with a disability	1960	2.41	27.06	10.3337	4.1456
% population of Hispanic or non-white race/ethnicity	1960	0.00	75.66	17.4559	13.8626

[a] These variables were measured using a quarter-mile network buffer.

3.7 Summary

This chapter summarized the entire process of data collection and assembly. First, three types of study locations were defined: segments or mid-block locations, non-signalized intersections, and signalized intersections. Next, crash data and exposure data were obtained from a variety of sources and processes; all crash and volume distributions were positively skewed. Then, information on roadway and community characteristics were assembled for study locations from existing databases. Finally, the datasets were combined and descriptive statistics were presented. These datasets are used for crash frequency modeling in the following chapter.

4.0 DATA ANALYSIS

4.1 Overview

This chapter presents results of the data analysis process. Results are shown for Poisson and negative binomial regression models, using roadway and community characteristics variables to predict pedestrian and bicycle crash frequencies. (These are sometimes called safety performance functions.) A total of 48 different models are shown, for different location types (segments or mid-block locations vs. non-signalized intersections vs. signalized intersections), different modes (pedestrian vs. bicycle), different crash types (all vs. fatal and serious injury), different facility types (state-only vs. state and federal-aid routes), and for different levels of data availability (with vs. without bicycle/pedestrian exposure). Next, model results are summarized and compared, identifying factors associated with more or fewer pedestrian and bicycle crashes.

4.2 Regression Modeling Approach for Risk Factor Determination

In order to identify risk factors as part of a systemic pedestrian and bicycle safety analysis, this project adopts the common method of modeling crash frequencies as a function of explanatory factors. As previously described in Section 2.3, Poisson regression is more appropriate than linear regression for modeling count data, and negative binomial (NB) regression is a generalization of the Poisson model that allows for data to be overdispersed (variance > mean), which is a common characteristic of crash frequency data.

For each situation described in the following sections, crash frequency regression models were estimated according to the following procedure. Both negative binomial and Poisson models were estimated. For each model, estimation used a backward elimination process to determine which explanatory variables described in Section 3.6 were retained in the model. This process first adds all of the independent variables to the model, removes the "least significant" variable (with the largest p-value), and estimates the model again. The process is repeated until all variables are at least marginally significant ($p < 0.10$). The only exception is that key variables (measures of exposure, length for segments, number of legs for non-signalized intersections and signalized intersections) were retained in the models no matter if they were statistically significant or not. Finally, the best-fitting NB and Poisson models were compared using a likelihood-ratio test (for nested models) or a Vuong test (for non-nested models), to determine which model was more appropriate (better fitting, considering the number of parameters). These are the models shown in this chapter. (Poisson models have a dispersion parameter equal to 1.00, while NB models do not.)

A few other comments about the models are warranted. Foremost, in all models, the measures of exposure (pedestrian volumes, Strava bicycle volumes, and motor vehicle traffic volumes) entered the model transformed using a natural log and with +1 added to the volume. This is done for several reasons. First, as shown in Section 3.4, the exposure data were skewed, so the natural log transformation reduces this skewness. Second, many volume data were close to zero, so taking the natural log of a value less than 1 would be negative; adding 1 to all volume values means that all log-transformed values are positive and starting from zero ($\ln(1) = 0$). Third, the use of a natural log transformation for these independent variables (along with the natural log transformation of the dependent variable inherent in Poisson or NB regression), means that coefficients for exposure can be interpreted as percentage changes in expected crashes for a 1% increase in the exposure variable. In other words, the relationship between crashes and exposure is proportional and relative to the baseline volume at a site. For example, if the coefficient on pedestrian volume was 0.50, then a 10% increase in pedestrian volume would be expected to increase crashes by 5%, no matter if the average pedestrian volume was 5 or 500 people per day. This is a common method in crash frequency modeling, including in the safety performance functions included in the Highway Safety Manual.

In addition, the variable segment length was included in all of the segment models, transformed using a natural log, and with a coefficient fixed at 1.00. (In modeling terminology, this is called an offset.) One reason is that the relationships are not affected by the extreme variations in the lengths of all of the segment locations (some are hundredths of a mile, while others are many miles long). Another reason for doing this is so that all of the relationships with crashes are on a per length basis. This is a common method in crash frequency modeling for segments or mid-block locations.

As mentioned in Section 2.3, crash frequency modeling using methods such as negative binomial regression are recommended practices for identifying risk factors. These models also act as safety performance functions (SPFs), identifying variables (and their weights) significantly associated with greater or fewer pedestrian and bicycle crashes. As will be shown in Chapter 5.0, the model results are useful for determining risk factors and identifying potential treatment locations as part of a systemic safety analysis.

The following sections summarize the estimated crash frequency models. Each model is named (e.g., B-NSig-KA-A) as described here. Separate sections are included for each mode (P = pedestrian vs. B = bicycle) and type of study location (Seg = segments and mid-block locations, NSig = non-signalized intersections, Sig = signalized intersections). Within each section, separate subsections are included for all crashes (All) vs. fatal and serious injury crashes only (KA). Within each of these subsections, four models are usually presented: models A and B are for locations on state-only roads (with and without pedestrian or bicycle exposure), while models C and D are for locations on state and federal-aid roads (again, with/out pedestrian or bicycle exposure). Four different models are presented for each location type and crash type combination because they use different sample sizes and list of independent variables (for larger sample sizes, fewer variables are available).

The following tables show regression model results, coefficient estimates, and significance levels. A positive (+) coefficient means that the variable is positively associated with pedestrian or bicycle crashes: an increase in that variable would be expected to result in more crashes. A negative (−) coefficient means that the variable is negatively associated with pedestrian or bicycle crashes: the model predicts that an increase in that variable would result in fewer crashes. For measures of exposure, a coefficient between 0 and 1 indicates a “safety-in-numbers” effect: the model predicts that an increase in exposure would result in fewer crashes per unit of exposure (vehicle, pedestrian, bicyclist). Following these model results tables are other sections summarizing the overall results and factors associated with pedestrian and bicycle crashes.

4.3 Pedestrian Crashes at Segments or Mid-Block Locations

4.3.1 All Crashes

4.3.1.1 State-Only Road Segments or Mid-Block Locations

Table 4.1 and Table 4.2 present the results of the NB models of all pedestrian crashes at state-only road segments or mid-block locations, with and without pedestrian exposure.

Table 4.1 Model P-Seg-All-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.5700	0.3360	4.67	<0.001
Offset: ln (segment length)	1.0000			
(Intercept)	-12.9254	0.7141	-18.101	<0.001
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.4720	0.0615	7.680	<0.001
Annual average daily traffic (AADT)	0.3669	0.0761	4.820	<0.001
Roadway geometry and traffic characteristics				
Truck proportion of AADT	1.3047	0.5284	2.469	0.014
One-way road segment	-0.6317	0.3008	-2.100	0.036
# two-way left-turn lanes	0.2301	0.0892	2.580	0.010
Presence of a right barrier	-0.4267	0.1708	-2.499	0.012
Driveways (# / km), commercial	0.0174	0.0027	6.534	<0.001
Driveways (# / km), industrial	0.0347	0.0092	3.751	<0.001
Driveways (# / km), residential	0.0057	0.0027	2.098	0.036
# bus stops	0.1079	0.0401	2.693	0.007
Neighborhood and community characteristics				
Employment density (jobs / acre)	-0.0198	0.0110	-1.798	0.072
% zero-vehicle households	0.0201	0.0099	2.027	0.043
% population with a disability	-0.0251	0.0054	-4.616	<0.001
% population of Hispanic or non-white race/ethnicity	0.0237	0.0033	7.129	<0.001
Model fit statistics				
Sample size (N)	5209			
Log-likelihood, fitted model	-1915.02			
Log-likelihood, intercept-only (null) model	-2399.57			
McFadden pseudo R^2 value	0.202			

[a] The natural log of these variables (+1) entered the model.
Model name: P = pedestrian, Seg = segments and mid-block locations, All = all crashes, A = state-only roads with pedestrian exposure.

Table 4.2 Model P-Seg-All-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.2210	0.2160	5.65	<0.001
Offset: ln (segment length)	1.0000			
(Intercept)	-16.1731	0.6312	-25.622	<0.001
Measures of exposure [a]				
Annual average daily traffic (AADT)	0.9882	0.0633	15.608	<0.001
Roadway geometry and traffic characteristics				
One-way road segment	-1.0445	0.3010	-3.470	0.001
# through lanes	-0.1069	0.0402	-2.659	0.008
# two-way left-turn lanes	0.1736	0.0828	2.097	0.036
Presence of rumble strips	-0.6649	0.1736	-3.830	<0.001
Presence of a right barrier	-0.3917	0.1435	-2.730	0.006
# bike lanes	-0.1566	0.0749	-2.091	0.037
Speed limit (mi / hr)	-0.0304	0.0053	-5.721	<0.001
Driveways (# / km), commercial	0.0232	0.0024	9.644	<0.001
Driveways (# / km), industrial	0.0354	0.0087	4.065	<0.001
Driveways (# / km), residential	0.0058	0.0027	2.198	0.028
# bus stops	0.1807	0.0382	4.732	<0.001
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.0964	0.0327	2.945	0.003
% zero-vehicle households	0.0269	0.0067	4.003	<0.001
% population with a disability	-0.0126	0.0050	-2.511	0.012
% population of Hispanic or non-white race/ethnicity	0.0181	0.0027	6.733	<0.001
Model fit statistics				
Sample size (N)	12638			
Log-likelihood, fitted model	-2553.24			
Log-likelihood, intercept-only (null) model	-3525.07			
McFadden pseudo R^2 value	0.276			

[a] The natural log of these variables (+1) entered the model.

Model name: P = pedestrian, Seg = segments and mid-block locations, All = all crashes, B = state-only roads without pedestrian exposure.

4.3.1.2 State and Federal-Aid Road Segments or Mid-Block Locations

Table 4.3 and Table 4.4 present the results of the NB models of all pedestrian crashes at state and federal-aid road segments or mid-block locations, with and without pedestrian exposure.

Table 4.3 Model P-Seg-All-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.8900	0.1100	8.09	<0.001
Offset: ln (segment length)	1.0000			
(Intercept)	-12.1722	0.3413	-35.665	<0.001
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.6936	0.0460	15.082	<0.001
Annual average daily traffic (AADT)	0.2548	0.0335	7.598	<0.001
Roadway geometry and traffic characteristics				
Interstate, US, or Utah numbered highway	0.4385	0.0706	6.214	<0.001
One-way road segment	-1.3296	0.1982	-6.710	<0.001
# bus stops	0.1575	0.0301	5.230	<0.001
# commuter rail stations (within 400 m)	0.7876	0.2215	3.556	<0.001
# light rail stations (within 400 m)	0.1892	0.0869	2.177	0.029
Neighborhood and community characteristics				
Residential density (housing units / acre)	-0.0482	0.0245	-1.966	0.049
Employment density (jobs / acre)	-0.0160	0.0073	-2.189	0.029
Jobs-housing balance (jobs / household)	-0.0089	0.0037	-2.372	0.018
Household income (median, $1,000)	-0.0027	0.0016	-1.705	0.088
% population with a disability	-0.0219	0.0042	-5.204	<0.001
% population of Hispanic or non-white race/ethnicity	0.0235	0.0025	9.464	<0.001
Model fit statistics				
Sample size (N)	20928			
Log-likelihood, fitted model	-4697.70			
Log-likelihood, intercept-only (null) model	-5888.49			
McFadden pseudo R^2 value	0.202			

[a] The natural log of these variables (+1) entered the model.
Model name: P = pedestrian, Seg = segments and mid-block locations, All = all crashes, C = state and federal aid roads with pedestrian exposure.

Table 4.4 Model P-Seg-All-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.6220	0.0629	9.89	<0.001
Offset: ln (segment length)	1.0000			
(Intercept)	-13.7361	0.2750	-49.942	<0.001
Measures of exposure [a]				
Annual average daily traffic (AADT)	0.7423	0.0282	26.308	<0.001
Roadway geometry and traffic characteristics				
Interstate, US, or Utah numbered highway	0.2829	0.0715	3.958	<0.001
One-way road segment	-0.9476	0.1490	-6.362	<0.001
Speed limit (mi / hr)	-0.0450	0.0031	-14.446	<0.001
# bus stops	0.3019	0.0298	10.141	<0.001
# commuter rail stations (within 400 m)	0.9962	0.2310	4.312	<0.001
# light rail stations (within 400 m)	0.3297	0.0916	3.598	<0.001
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.1868	0.0179	10.448	<0.001
Employment density (jobs / acre)	0.0203	0.0065	3.133	0.002
Jobs-housing balance (jobs / household)	-0.0069	0.0034	-2.020	0.043
Household income (median, $1,000)	-0.0052	0.0014	-3.606	<0.001
% population of Hispanic or non-white race/ethnicity	0.0196	0.0019	10.351	<0.001
Model fit statistics				
Sample size (N)	34094			
Log-likelihood, fitted model	-6025.84			
Log-likelihood, intercept-only (null) model	-7509.32			
McFadden pseudo R^2 value	0.198			

[a] The natural log of these variables (+1) entered the model.

Model name: P = pedestrian, Seg = segments and mid-block locations, All = all crashes, D = state and federal aid roads without pedestrian exposure.

4.3.2 Fatal and Serious Injury Crashes

4.3.2.1 State-Only Road Segments or Mid-Block Locations

Table 4.5 and Table 4.6 present the results of the NB models of fatal and serious injury pedestrian crashes at state-only road segments or mid-block locations, with and without pedestrian exposure.

Table 4.5 Model P-Seg-KA-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.5970	0.9140	1.75	0.087
Offset: ln (segment length)	1.0000			
(Intercept)	-15.9548	1.2883	-12.385	<0.001
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.4243	0.1027	4.133	<0.001
Annual average daily traffic (AADT)	0.5539	0.1331	4.162	<0.001
Roadway geometry and traffic characteristics				
Truck proportion of AADT	2.7576	0.8881	3.105	0.002
# right-turn lanes	-0.1474	0.0865	-1.704	0.088
# two-way left-turn lanes	0.2621	0.1493	1.756	0.079
Presence of a right shoulder	0.2798	0.1670	1.675	0.094
Presence of a right barrier	-0.6783	0.2926	-2.318	0.020
# bike lanes	-0.2606	0.1512	-1.724	0.085
Driveways (# / km), commercial	0.0161	0.0045	3.539	<0.001
Driveways (# / km), residential	0.0099	0.0042	2.365	0.018
# bus stops	0.1451	0.0652	2.228	0.026
Neighborhood and community characteristics				
Employment density (jobs / acre)	-0.0818	0.0209	-3.915	<0.001
% zero-vehicle households	0.0571	0.0159	3.590	<0.001
% population with a disability	-0.0303	0.0102	-2.967	0.003
% population of Hispanic or non-white race/ethnicity	0.0270	0.0058	4.678	<0.001
Model fit statistics				
Sample size (N)	5209			
Log-likelihood, fitted model	-854.95			
Log-likelihood, intercept-only (null) model	-1007.46			
McFadden pseudo R^2 value	0.151			

[a] The natural log of these variables (+1) entered the model.
Model name: P = pedestrian, Seg = segments and mid-block locations, KA = fatal and serious injury crashes, A = state-only roads with pedestrian exposure.

Table 4.6 Model P-Seg-KA-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.9730	0.3850	2.53	0.016
Offset: ln (segment length)	1.0000			
(Intercept)	-18.0698	1.0937	-16.522	<0.001
Measures of exposure [a]				
Annual average daily traffic (AADT)	1.0376	0.0821	12.639	<0.001
Roadway geometry and traffic characteristics				
Truck proportion of AADT	1.2705	0.6793	1.870	0.061
Presence of rumble strips	-0.6110	0.2640	-2.314	0.021
Presence of a right barrier	-0.5766	0.2350	-2.453	0.014
Percentage grade	0.1023	0.0479	2.136	0.033
Speed limit (mi / hr)	-0.0174	0.0088	-1.971	0.049
Driveways (# / km), commercial	0.0230	0.0041	5.654	<0.001
Driveways (# / km), residential	0.0138	0.0039	3.556	<0.001
# bus stops	0.2462	0.0603	4.082	<0.001
Neighborhood and community characteristics				
Employment density (jobs / acre)	-0.0650	0.0187	-3.478	0.001
Household income (median, $1,000)	-0.0088	0.0040	-2.219	0.027
% zero-vehicle households	0.0542	0.0157	3.456	0.001
% population with a disability	-0.0216	0.0085	-2.531	0.011
% population of Hispanic or non-white race/ethnicity	0.0170	0.0041	4.087	<0.001
Model fit statistics				
Sample size (N)	11723			
Log-likelihood, fitted model	-1122.92			
Log-likelihood, intercept-only (null) model	-1415.84			
McFadden pseudo R^2 value	0.207			

[a] The natural log of these variables (+1) entered the model.

Model name: P = pedestrian, Seg = segments and mid-block locations, KA = fatal and serious injury crashes, B = state-only roads without pedestrian exposure.

4.3.2.2 State and Federal-Aid Road Segments or Mid-Block Locations

Table 4.7 and Table 4.8 present the results of the NB models of fatal and serious injury pedestrian crashes at state and federal-aid road segments or mid-block locations, with and without pedestrian exposure.

Table 4.7 Model P-Seg-KA-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.6250	0.1790	3.49	0.001
Offset: ln (segment length)	1.0000			
(Intercept)	-14.0373	0.5908	-23.762	<0.001
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.4606	0.0673	6.843	<0.001
Annual average daily traffic (AADT)	0.3516	0.0659	5.335	<0.001
Roadway geometry and traffic characteristics				
Interstate, US, or Utah numbered highway	0.6774	0.1258	5.385	<0.001
One-way road segment	-0.9990	0.2748	-3.635	<0.001
# bus stops	0.2502	0.0483	5.185	<0.001
# commuter rail stations (within 400 m)	1.2213	0.3313	3.686	<0.001
Neighborhood and community characteristics				
Employment density (jobs / acre)	-0.0302	0.0154	-1.963	0.050
Jobs-housing balance (jobs / household)	-0.0103	0.0059	-1.739	0.082
% zero-vehicle households	0.0222	0.0124	1.792	0.073
% population with a disability	-0.0255	0.0071	-3.571	<0.001
% population of Hispanic or non-white race/ethnicity	0.0279	0.0041	6.739	<0.001
Model fit statistics				
Sample size (N)	21673			
Log-likelihood, fitted model	-1838.00			
Log-likelihood, intercept-only (null) model	-2204.60			
McFadden pseudo R^2 value	0.166			

[a] The natural log of these variables (+1) entered the model.
Model name: P = pedestrian, Seg = segments and mid-block locations, KA = fatal and serious injury crashes, C = state and federal aid roads with pedestrian exposure.

Table 4.8 Model P-Seg-KA-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.4950	0.1170	4.23	<0.001
Offset: ln (segment length)	1.0000			
(Intercept)	-16.3362	0.4782	-34.164	<0.001
Measures of exposure [a]				
Annual average daily traffic (AADT)	0.7889	0.0482	16.368	<0.001
Roadway geometry and traffic characteristics				
Interstate, US, or Utah numbered highway	0.5191	0.1233	4.211	<0.001
One-way road segment	-0.8418	0.2255	-3.733	<0.001
Speed limit (mi / hr)	-0.0359	0.0052	-6.908	<0.001
# bus stops	0.3379	0.0457	7.389	<0.001
# commuter rail stations (within 400 m)	1.1804	0.3413	3.458	0.001
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.1606	0.0301	5.338	<0.001
% zero-vehicle households	0.0260	0.0078	3.323	0.001
% population of Hispanic or non-white race/ethnicity	0.0191	0.0029	6.614	<0.001
Model fit statistics				
Sample size (N)	36173			
Log-likelihood, fitted model	-2408.96			
Log-likelihood, intercept-only (null) model	-2918.04			
McFadden pseudo R^2 value	0.174			

[a] The natural log of these variables (+1) entered the model.
Model name: P = pedestrian, Seg = segments and mid-block locations, KA = fatal and serious injury crashes, D = state and federal aid roads without pedestrian exposure.

4.4 Bicycle Crashes at Segments or Mid-Block Locations

4.4.1 All Crashes

4.4.1.1 State-Only Road Segments or Mid-Block Locations

Table 4.9 and Table 4.10 present the results of the NB models of all bicycle crashes at state-only road segments or mid-block locations, with and without bicycle exposure.

Table 4.9 Model B-Seg-All-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.5010	0.3140	4.78	<0.001
Offset: ln (segment length)	1.0000			
(Intercept)	-14.3066	0.8388	-17.056	<0.001
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	0.3641	0.0599	6.076	<0.001
Annual average daily traffic (AADT)	0.7711	0.0609	12.663	<0.001
Roadway geometry and traffic characteristics				
Through lane width (ft)	-0.0968	0.0432	-2.240	0.025
# left-turn lanes	0.2117	0.0424	4.987	<0.001
Presence of a median	-0.3334	0.1077	-3.095	0.002
Presence of rumble strips	-1.3777	0.2800	-4.920	<0.001
Presence of a right barrier	-0.7610	0.1817	-4.188	<0.001
Percentage grade	0.1159	0.0282	4.110	<0.001
Speed limit (mi / hr)	-0.0343	0.0063	-5.438	<0.001
Driveways (# / km), commercial	0.0313	0.0024	13.155	<0.001
Driveways (# / km), industrial	0.0336	0.0097	3.471	0.001
Driveways (# / km), residential	0.0049	0.0030	1.651	0.099
# bus stops	0.0954	0.0414	2.306	0.021
# commuter rail stations (within 400 m)	0.8019	0.4403	1.821	0.069
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.1418	0.0304	4.664	<0.001
Employment density (jobs / acre)	0.0312	0.0069	4.500	<0.001
% population of Hispanic or non-white race/ethnicity	0.0118	0.0035	3.362	0.001
Model fit statistics				
Sample size (N)	11832			
Log-likelihood, fitted model	-2090.29			
Log-likelihood, intercept-only (null) model	-3058.08			
McFadden pseudo R^2 value	0.316			

[a] The natural log of these variables (+1) entered the model.
Model name: B = bicycle, Seg = segments and mid-block locations, All = all crashes, A = state-only roads with bicycle exposure.

Table 4.10 Model B-Seg-All-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.4540	0.2990	4.86	<0.001
Offset: ln (segment length)	1.0000			
(Intercept)	-14.2090	0.8305	-17.109	<0.001
Measures of exposure [a]				
Annual average daily traffic (AADT)	0.8451	0.0589	14.337	<0.001
Roadway geometry and traffic characteristics				
Elevated road segment	-1.2685	0.6033	-2.102	0.036
Through lane width (ft)	-0.1185	0.0448	-2.646	0.008
# left-turn lanes	0.1941	0.0414	4.689	<0.001
Presence of a median	-0.3568	0.1057	-3.377	0.001
Presence of rumble strips	-1.3827	0.2579	-5.362	<0.001
Presence of a right barrier	-0.6057	0.1717	-3.528	<0.001
# bike lanes	0.1118	0.0659	1.695	0.090
Percentage grade	0.1276	0.0277	4.609	<0.001
Speed limit (mi / hr)	-0.0360	0.0060	-5.968	<0.001
Driveways (# / km), commercial	0.0300	0.0024	12.751	<0.001
Driveways (# / km), industrial	0.0333	0.0096	3.481	<0.001
Driveways (# / km), residential	0.0049	0.0029	1.681	0.093
# bus stops	0.0956	0.0407	2.350	0.019
# commuter rail stations (within 400 m)	1.0539	0.4473	2.356	0.018
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.1312	0.0304	4.323	<0.001
Employment density (jobs / acre)	0.0388	0.0068	5.724	<0.001
Model fit statistics				
Sample size (N)	12578			
Log-likelihood, fitted model	-2184.26			
Log-likelihood, intercept-only (null) model	-3170.96			
McFadden pseudo R^2 value	0.311			

[a] The natural log of these variables (+1) entered the model.
Model name: B = bicycle, Seg = segments and mid-block locations, All = all crashes, B = state-only roads without bicycle exposure.

4.4.1.2 State and Federal-Aid Road Segments or Mid-Block Locations

Table 4.11 and Table 4.12 present the results of the NB models of all bicycle crashes at state and federal-aid road segments or mid-block locations, with and without bicycle exposure.

Table 4.11 Model B-Seg-All-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.7338	0.0847	8.66	<0.001
Offset: ln (segment length)	1.0000			
(Intercept)	-14.2263	0.3525	-40.357	<0.001
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	0.4157	0.0452	9.206	<0.001
Annual average daily traffic (AADT)	0.7912	0.0341	23.202	<0.001
Roadway geometry and traffic characteristics				
Interstate, US, or Utah numbered highway	0.3744	0.0774	4.836	<0.001
One-way road segment	-2.0088	0.2965	-6.775	<0.001
Elevated road segment	-1.2417	0.4407	-2.818	0.005
Speed limit (mi / hr)	-0.0518	0.0038	-13.544	<0.001
# bus stops	0.2631	0.0307	8.580	<0.001
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.1877	0.0180	10.435	<0.001
Employment density (jobs / acre)	0.0361	0.0049	7.344	<0.001
Household income (median, $1,000)	-0.0051	0.0016	-3.202	0.001
% population with a disability	-0.0086	0.0038	-2.288	0.022
% population of Hispanic or non-white race/ethnicity	0.0139	0.0024	5.883	<0.001
Model fit statistics				
Sample size (N)	31710			
Log-likelihood, fitted model	-4866.15			
Log-likelihood, intercept-only (null) model	-6296.41			
McFadden pseudo R^2 value	0.227			

[a] The natural log of these variables (+1) entered the model.
Model name: B = bicycle, Seg = segments and mid-block locations, All = all crashes, C = state and federal aid roads with bicycle exposure.

Table 4.12 Model B-Seg-All-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.6635	0.0706	9.40	<0.001
Offset: ln (segment length)	1.0000			
(Intercept)	-14.6320	0.3142	-46.566	<0.001
Measures of exposure [a]				
Annual average daily traffic (AADT)	0.8454	0.0313	27.029	<0.001
Roadway geometry and traffic characteristics				
Interstate, US, or Utah numbered highway	0.3210	0.0733	4.378	<0.001
One-way road segment	-2.1182	0.2610	-8.114	<0.001
Elevated road segment	-1.5301	0.4362	-3.508	<0.001
Speed limit (mi / hr)	-0.0541	0.0036	-15.211	<0.001
# bus stops	0.2506	0.0303	8.285	<0.001
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.2069	0.0171	12.087	<0.001
Employment density (jobs / acre)	0.0464	0.0046	10.084	<0.001
% population with a disability	-0.0063	0.0036	-1.749	0.080
% population of Hispanic or non-white race/ethnicity	0.0099	0.0022	4.541	0.000
Model fit statistics				
Sample size (N)	36173			
Log-likelihood, fitted model	-5410.96			
Log-likelihood, intercept-only (null) model	-6993.20			
McFadden pseudo R^2 value	0.226			

[a] The natural log of these variables (+1) entered the model.

Model name: B = bicycle, Seg = segments and mid-block locations, All = all crashes, D = state and federal aid roads without bicycle exposure.

4.4.2 Fatal and Serious Injury Crashes

4.4.2.1 State-Only Road Segments or Mid-Block Locations

Table 4.13 and Table 4.14 present the results of the Poisson models of fatal and serious injury bicycle crashes at state-only road segments or mid-block locations, with and without bicycle exposure.

Table 4.13 Model B-Seg-KA-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
Offset: ln (segment length)	1.0000			
(Intercept)	-11.8720	1.8493	-6.420	<0.001
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	0.7556	0.1583	4.772	<0.001
Annual average daily traffic (AADT)	0.6431	0.1288	4.994	<0.001
Roadway geometry and traffic characteristics				
Through lane width (ft)	-0.3427	0.1013	-3.382	0.001
Presence of rumble strips	-1.1377	0.5571	-2.042	0.041
Percentage grade	0.2161	0.0588	3.676	<0.001
Speed limit (mi / hr)	-0.0251	0.0147	-1.709	0.088
Driveways (# / km), commercial	0.0186	0.0075	2.494	0.013
Driveways (# / km), residential	0.0159	0.0062	2.558	0.011
# bus stops	0.3053	0.0970	3.146	0.002
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.1352	0.0731	1.851	0.064
Household income (median, $1,000)	-0.0147	0.0057	-2.573	0.010
Model fit statistics				
Sample size (N)	11034			
Log-likelihood, fitted model	-429.89			
Log-likelihood, intercept-only (null) model	-510.12			
McFadden pseudo R^2 value	0.157			

[a] The natural log of these variables (+1) entered the model.
Model name: B = bicycle, Seg = segments and mid-block locations, KA = fatal and serious injury crashes, A = state-only roads with bicycle exposure.

Table 4.14 Model B-Seg-KA-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
Offset: ln (segment length)	1.0000			
(Intercept)	-12.5263	1.7653	-7.096	<0.001
Measures of exposure [a]				
Annual average daily traffic (AADT)	0.7041	0.1257	5.603	<0.001
Roadway geometry and traffic characteristics				
Through lane width (ft)	-0.3476	0.0899	-3.865	<0.001
Presence of a median	-0.6473	0.3101	-2.087	0.037
Presence of rumble strips	-1.3384	0.5537	-2.417	0.016
Presence of a right barrier	-0.8041	0.4213	-1.909	0.056
# bike lanes	0.3273	0.1556	2.104	0.035
Percentage grade	0.2387	0.0570	4.185	<0.001
Speed limit (mi / hr)	-0.0249	0.0138	-1.800	0.072
Driveways (# / km), commercial	0.0162	0.0072	2.259	0.024
Driveways (# / km), residential	0.0132	0.0061	2.163	0.031
# bus stops	0.2229	0.0968	2.304	0.021
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.2004	0.0688	2.912	0.004
Model fit statistics				
Sample size (N)	12578			
Log-likelihood, fitted model	-467.17			
Log-likelihood, intercept-only (null) model	-556.05			
McFadden pseudo R^2 value	0.160			

[a] The natural log of these variables (+1) entered the model.

Model name: B = bicycle, Seg = segments and mid-block locations, KA = fatal and serious injury crashes, B = state-only roads without bicycle exposure.

4.4.2.2 State and Federal-Aid Road Segments or Mid-Block Locations

Table 4.15 and Table 4.16 present the results of the NB models of fatal and serious injury bicycle crashes at state and federal-aid road segments or mid-block locations, with and without bicycle exposure.

Table 4.15 Model B-Seg-KA-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.8260	0.7000	1.18	0.199
Offset: ln (segment length)	1.0000			
(Intercept)	-14.6778	0.8632	-17.005	<0.001
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	0.7629	0.1065	7.162	<0.001
Annual average daily traffic (AADT)	0.6346	0.0831	7.637	<0.001
Roadway geometry and traffic characteristics				
Interstate, US, or Utah numbered highway	0.5576	0.2027	2.751	0.006
One-way road segment	-1.6917	0.7555	-2.239	0.025
Speed limit (mi / hr)	-0.0527	0.0098	-5.387	<0.001
# bus stops	0.2140	0.0781	2.738	0.006
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.1728	0.0476	3.634	<0.001
Household income (median, $1,000)	-0.0067	0.0036	-1.830	0.067
% population with a disability	-0.0165	0.0096	-1.721	0.085
Model fit statistics				
Sample size (N)	31710			
Log-likelihood, fitted model	-938.46			
Log-likelihood, intercept-only (null) model	-1082.91			
McFadden pseudo R^2 value	0.133			

[a] The natural log of these variables (+1) entered the model.
Model name: B = bicycle, Seg = segments and mid-block locations, KA = fatal and serious injury crashes, C = state and federal aid roads with bicycle exposure.

Table 4.16 Model B-Seg-KA-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.7410	0.6080	1.22	0.190
Offset: ln (segment length)	1.0000			
(Intercept)	-14.7869	0.8133	-18.181	<0.001
Measures of exposure [a]				
Annual average daily traffic (AADT)	0.6946	0.0779	8.917	<0.001
Roadway geometry and traffic characteristics				
Interstate, US, or Utah numbered highway	0.4706	0.1969	2.390	0.017
One-way road segment	-1.8594	0.6299	-2.952	0.003
Speed limit (mi / hr)	-0.0572	0.0090	-6.342	<0.001
# bus stops	0.2159	0.0770	2.803	0.005
Neighborhood and community characteristics				
Residential density (housing units / acre)	0.1930	0.0480	4.018	<0.001
Household income (median, $1,000)	0.0059	0.0032	1.837	0.066
% population with a disability	-0.0281	0.0101	-2.781	0.005
Model fit statistics				
Sample size (N)	34094			
Log-likelihood, fitted model	-1000.73			
Log-likelihood, intercept-only (null) model	-1132.33			
McFadden pseudo R^2 value	0.116			

[a] The natural log of these variables (+1) entered the model.

Model name: B = bicycle, Seg = segments and mid-block locations, KA = fatal and serious injury crashes, D = state and federal aid roads without bicycle exposure.

4.5 Pedestrian Crashes at Non-Signalized Intersections

4.5.1 All Crashes

4.5.1.1 Non-Signalized Intersections on State-Only Roads

Table 4.17 and Table 4.18 present the results of the NB models of all pedestrian crashes at non-signalized intersections on state-only roads, with and without pedestrian exposure.

Table 4.17 Model P-NSig-All-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.4150	0.2520	1.65	0.103
(Intercept)	-6.3943	2.4659	-2.593	0.010
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.7414	0.2072	3.578	<0.001
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.0641	0.3408	0.188	0.851
Transportation characteristics				
# intersection legs or approaches	0.9826	0.1780	5.519	<0.001
# through lanes, major direction	-0.3211	0.1726	-1.860	0.063
Speed limit (mi / hr) (maximum of legs)	-0.0548	0.0300	-1.825	0.068
Land use and built-environment characteristics				
Sociodemographic characteristics				
Model fit statistics				
Sample size (N)	1072			
Log-likelihood, fitted model	-129.53			
Log-likelihood, intercept-only (null) model	-162.45			
McFadden pseudo R^2 value	0.203			

[a] The natural log of these variables (+1) entered the model.
Model name: P = pedestrian, NSig = non-signalized intersections, All = all crashes, A = state-only roads with pedestrian exposure.

Table 4.18 Model P-NSig-All-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.1906	0.0732	2.60	0.013
(Intercept)	-7.2279	2.1982	-3.288	0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.5338	0.2208	2.417	0.016
Transportation characteristics				
# intersection legs or approaches	1.2371	0.1866	6.628	<0.001
Shoulder width (ft), major direction	0.1212	0.0508	2.385	0.017
Speed limit (mi / hr) (maximum of legs)	-0.1298	0.0289	-4.487	<0.001
Land use and built-environment characteristics				
Residential density (housing units / acre)	0.4158	0.1468	2.833	0.005
Sociodemographic characteristics				
Household income (median, $1,000)	-0.0162	0.0097	-1.678	0.093
Model fit statistics				
Sample size (N)	3045			
Log-likelihood, fitted model	-167.81			
Log-likelihood, intercept-only (null) model	-256.04			
McFadden pseudo R^2 value	0.345			

[a] The natural log of these variables (+1) entered the model.
Model name: P = pedestrian, NSig = non-signalized intersections, All = all crashes, B = state-only roads without pedestrian exposure.

4.5.1.2 Non-Signalized Intersections on State and Federal-Aid Roads

Table 4.19 and Table 4.20 present the results of the NB models of all pedestrian crashes at non-signalized intersections on state and federal-aid roads, with and without pedestrian exposure.

Table 4.19 Model P-NSig-All-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.4088	0.0457	8.95	<0.001
(Intercept)	-11.4506	0.4853	-23.594	<0.001
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.6913	0.0535	12.927	<0.001
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.2845	0.0315	9.032	<0.001
Transportation characteristics				
# intersection legs or approaches	0.9751	0.0537	18.147	<0.001
Presence of a bike lane	-0.2493	0.0990	-2.517	0.012
# of bus stops	0.2169	0.0558	3.887	<0.001
Land use and built-environment characteristics				
Employment density (1,000 jobs / mi^2)	-0.0251	0.0098	-2.572	0.010
Sociodemographic characteristics				
Household income (median, $1,000)	-0.0038	0.0019	-2.004	0.045
% population with a disability	0.0079	0.0047	1.695	0.090
% population of Hispanic or non-white race/ethnicity	0.0076	0.0030	2.515	0.012
Model fit statistics				
Sample size (N)	18983			
Log-likelihood, fitted model	-3702.23			
Log-likelihood, intercept-only (null) model	-4430.55			
McFadden pseudo R^2 value	0.164			

[a] The natural log of these variables (+1) entered the model.
Model name: P = pedestrian, NSig = non-signalized intersections, All = all crashes, C = state and federal aid roads with pedestrian exposure.

Table 4.20 Model P-NSig-All-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.3278	0.0329	9.96	<0.001
(Intercept)	-10.9403	0.4039	-27.088	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.5832	0.0333	17.509	<0.001
Transportation characteristics				
# intersection legs or approaches	1.0651	0.0522	20.410	<0.001
Presence of a bike lane	-0.3252	0.1023	-3.178	0.001
Speed limit (mi / hr) (maximum of legs)	-0.0328	0.0042	-7.870	<0.001
Distance (km) to nearest intersection	-2.1728	0.4666	-4.656	<0.001
# of bus stops	0.3879	0.0547	7.095	<0.001
# commuter rail stations (within 400 m)	0.8649	0.4296	2.013	0.044
Land use and built-environment characteristics				
Residential density (housing units / acre)	0.2147	0.0221	9.714	<0.001
Sociodemographic characteristics				
Household income (median, $1,000)	-0.0068	0.0017	-4.027	<0.001
% population with a disability	0.0148	0.0048	3.090	0.002
% population of Hispanic or non-white race/ethnicity	0.0134	0.0026	5.098	<0.001
Model fit statistics				
Sample size (N)	35787			
Log-likelihood, fitted model	-4284.36			
Log-likelihood, intercept-only (null) model	-5537.24			
McFadden pseudo R^2 value	0.226			

[a] The natural log of these variables (+1) entered the model.

Model name: P = pedestrian, NSig = non-signalized intersections, All = all crashes, D = state and federal aid roads without pedestrian exposure.

4.5.2 Fatal and Serious Injury Crashes

4.5.2.1 Non-Signalized Intersections on State-Only Roads

Table 4.21 and Table 4.22 present the results of the Poisson models of fatal and serious injury pedestrian crashes at non-signalized intersections on state-only roads, with and without pedestrian exposure.

Table 4.21 Model P-NSig-KA-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-12.0664	5.1546	-2.341	0.019
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	1.2629	0.6026	2.096	0.036
Annual average daily traffic, major direction ($AADT_{MAJ}$)	-0.2333	0.4470	-0.522	0.602
Transportation characteristics				
# intersection legs or approaches	1.0907	0.3791	2.877	0.004
Land use and built-environment characteristics				
Sociodemographic characteristics				
Model fit statistics				
Sample size (N)	1147			
Log-likelihood, fitted model	-21.40			
Log-likelihood, intercept-only (null) model	-26.63			
McFadden pseudo R^2 value	0.197			

[a] The natural log of these variables (+1) entered the model.
Model name: P = pedestrian, NSig = non-signalized intersections, KA = fatal and serious injury crashes, A = state-only roads with pedestrian exposure.

Table 4.22 Model P-NSig-KA-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-13.2580	5.0744	-2.613	0.009
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.9567	0.6098	1.569	0.117
Transportation characteristics				
# intersection legs or approaches	1.0420	0.3189	3.267	0.001
Speed limit (mi / hr) (maximum of legs)	-0.1295	0.0628	-2.061	0.039
# of bus stops	0.8678	0.4978	1.743	0.081
Land use and built-environment characteristics				
Sociodemographic characteristics				
Model fit statistics				
Sample size (N)	3359			
Log-likelihood, fitted model	-27.66			
Log-likelihood, intercept-only (null) model	-37.55			
McFadden pseudo R^2 value	0.264			

[a] The natural log of these variables (+1) entered the model.

Model name: P = pedestrian, NSig = non-signalized intersections, KA = fatal and serious injury crashes, B = state-only roads without pedestrian exposure.

4.5.2.2 Non-Signalized Intersections on State and Federal-Aid Roads

Table 4.23 and Table 4.24 present the results of the Poisson and NB models of fatal and serious injury pedestrian crashes at non-signalized intersections on state and federal-aid roads, with and without pedestrian exposure.

Table 4.23 Model P-NSig-KA-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-11.4209	0.9079	-12.580	<0.001
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.4831	0.1070	4.517	<0.001
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.3936	0.0718	5.485	<0.001
Transportation characteristics				
# intersection legs or approaches	0.6992	0.1067	6.552	<0.001
# of bus stops	0.4222	0.1027	4.110	<0.001
Land use and built-environment characteristics				
Employment density (1,000 jobs / mi^2)	-0.0885	0.0275	-3.212	0.001
Sociodemographic characteristics				
Household income (median, $1,000)	-0.0119	0.0040	-2.974	0.003
Model fit statistics				
Sample size (N)	18983			
Log-likelihood, fitted model	-965.32			
Log-likelihood, intercept-only (null) model	-1063.38			
McFadden pseudo R^2 value	0.092			

[a] The natural log of these variables (+1) entered the model.

Model name: P = pedestrian, NSig = non-signalized intersections, KA = fatal and serious injury crashes, C = state and federal aid roads with pedestrian exposure.

Table 4.24 Model P-NSig-KA-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.4470	0.2500	1.79	0.081
(Intercept)	-11.4556	0.8149	-14.058	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.6063	0.0810	7.487	<0.001
Transportation characteristics				
# intersection legs or approaches	0.8617	0.1037	8.313	<0.001
Speed limit (mi / hr) (maximum of legs)	-0.0191	0.0093	-2.056	0.040
Distance (km) to nearest intersection	-2.1722	0.9777	-2.222	0.026
Distance (km) to nearest signal	-0.0334	0.0183	-1.826	0.068
# of bus stops	0.5825	0.0991	5.877	<0.001
Land use and built-environment characteristics				
Jobs-housing balance (jobs / household)	-0.0401	0.0155	-2.589	0.010
Sociodemographic characteristics				
Household income (median, $1,000)	-0.0126	0.0037	-3.381	0.001
% population of Hispanic or non-white race/ethnicity	0.0165	0.0057	2.880	0.004
Model fit statistics				
Sample size (N)	35787			
Log-likelihood, fitted model	-1096.06			
Log-likelihood, intercept-only (null) model	-1288.45			
McFadden pseudo R^2 value	0.149			

[a] The natural log of these variables (+1) entered the model.

Model name: P = pedestrian, NSig = non-signalized intersections, KA = fatal and serious injury crashes, D = state and federal aid roads without pedestrian exposure.

4.6 Bicycle Crashes at Non-Signalized Intersections

4.6.1 All Crashes

4.6.1.1 Non-Signalized Intersections on State-Only Roads

Table 4.25 and Table 4.26 present the results of the Poisson models of all bicycle crashes at non-signalized intersections on state-only roads, with and without bicycle exposure.

Table 4.25 Model B-NSig-All-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-5.2016	2.6691	-1.949	0.051
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	-0.2984	0.2672	-1.117	0.264
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.3119	0.2572	1.213	0.225
Truck proportion of $AADT_{MAJ}$	-4.4076	2.0269	-2.175	0.030
Transportation characteristics				
# intersection legs or approaches	0.8366	0.1476	5.668	<0.001
# left-turn lanes, major direction	-0.3983	0.1755	-2.270	0.023
# right-turn lanes, major direction	0.6147	0.2676	2.297	0.022
Median width (ft), major direction	-0.0934	0.0314	-2.978	0.003
Distance (km) to nearest intersection	1.3786	0.5260	2.621	0.009
Distance (km) to nearest signal	-0.4193	0.1890	-2.219	0.026
# commuter rail stations (within 400 m)	1.5261	0.6031	2.530	0.011
Land use and built-environment characteristics				
Sociodemographic characteristics				
Household income (median, $1,000)	-0.0268	0.0084	-3.191	0.001
Model fit statistics				
Sample size (N)	1469			
Log-likelihood, fitted model	-135.61			
Log-likelihood, intercept-only (null) model	-190.21			
McFadden pseudo R^2 value	0.287			

[a] The natural log of these variables (+1) entered the model.
Model name: B = bicycle, NSig = non-signalized intersections, All = all crashes, A = state-only roads with bicycle exposure.

Table 4.26 Model B-NSig-All-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-15.6088	2.2465	-6.948	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	1.1228	0.2382	4.714	<0.001
Truck proportion of $AADT_{MAJ}$	-4.3978	1.8270	-2.407	0.016
Transportation characteristics				
# intersection legs or approaches	0.9012	0.1276	7.062	<0.001
# through lanes, major direction	-0.2952	0.1322	-2.232	0.026
Median width (ft), major direction	-0.1050	0.0265	-3.965	<0.001
Percentage grade (maximum of legs)	-0.3155	0.1129	-2.795	0.005
# commuter rail stations (within 400 m)	1.7243	0.5852	2.946	0.003
Land use and built-environment characteristics				
Residential density (housing units / acre)	0.4539	0.1211	3.748	<0.001
Sociodemographic characteristics				
% zero-vehicle households	0.0469	0.0256	1.830	0.067
% population with a disability	0.0403	0.0159	2.540	0.011
% population of Hispanic or non-white race/ethnicity	-0.0285	0.0161	-1.774	0.076
Model fit statistics				
Sample size (N)	3156			
Log-likelihood, fitted model	-191.11			
Log-likelihood, intercept-only (null) model	-272.08			
McFadden pseudo R^2 value	0.298			

[a] The natural log of these variables (+1) entered the model.

Model name: B = bicycle, NSig = non-signalized intersections, All = all crashes, B = state-only roads without bicycle exposure.

4.6.1.2 Non-Signalized Intersections on State and Federal-Aid Roads

Table 4.27 and Table 4.28 present the results of the NB and Poisson models of all bicycle crashes at non-signalized intersections on state and federal-aid roads, with and without bicycle exposure.

Table 4.27 Model B-NSig-All-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	0.5736	0.0757	7.58	<0.001
(Intercept)	-9.1414	0.3444	-26.545	<0.001
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	0.0067	0.0405	0.166	0.868
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4207	0.0378	11.116	<0.001
Transportation characteristics				
# intersection legs or approaches	0.8744	0.0495	17.667	<0.001
Presence of a bike lane	0.1400	0.0829	1.689	0.091
Speed limit (mi / hr) (maximum of legs)	-0.0155	0.0046	-3.362	0.001
Distance (km) to nearest signal	-0.1776	0.0370	-4.800	<0.001
# of bus stops	0.2630	0.0537	4.896	<0.001
Land use and built-environment characteristics				
Residential density (housing units / acre)	0.0797	0.0196	4.067	<0.001
Employment density (1,000 jobs / mi^2)	0.0346	0.0069	4.997	<0.001
Sociodemographic characteristics				
% population of Hispanic or non-white race/ethnicity	0.0120	0.0025	4.723	<0.001
Model fit statistics				
Sample size (N)	21643			
Log-likelihood, fitted model	-3928.67			
Log-likelihood, intercept-only (null) model	-4664.93			
McFadden pseudo R^2 value	0.158			

[a] The natural log of these variables (+1) entered the model.
Model name: B = bicycle, NSig = non-signalized intersections, All = all crashes, C = state and federal aid roads with bicycle exposure.

Table 4.28 Model B-NSig-All-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-9.6260	0.3387	-28.421	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4822	0.0319	15.124	<0.001
Transportation characteristics				
# intersection legs or approaches	0.8243	0.0367	22.457	<0.001
Presence of a bike lane	0.1606	0.0709	2.266	0.023
Speed limit (mi / hr) (maximum of legs)	-0.0173	0.0039	-4.419	<0.001
Distance (km) to nearest intersection	-0.5571	0.3269	-1.705	0.088
Distance (km) to nearest signal	-0.1562	0.0254	-6.153	<0.001
# of bus stops	0.2921	0.0420	6.962	<0.001
# commuter rail stations (within 400 m)	0.7141	0.2631	2.714	0.007
Land use and built-environment characteristics				
Residential density (housing units / acre)	0.1267	0.0172	7.351	<0.001
Employment density (1,000 jobs / mi^2)	0.0343	0.0058	5.942	<0.001
Sociodemographic characteristics				
Household income (median, $1,000)	-0.0032	0.0014	-2.358	0.018
% population with a disability	0.0115	0.0038	2.997	0.003
% population of Hispanic or non-white race/ethnicity	0.0074	0.0023	3.218	0.001
Model fit statistics				
Sample size (N)	35787			
Log-likelihood, fitted model	-4922.35			
Log-likelihood, intercept-only (null) model	-6197.88			
McFadden pseudo R^2 value	0.206			

[a] The natural log of these variables (+1) entered the model.

Model name: B = bicycle, NSig = non-signalized intersections, All = all crashes, D = state and federal aid roads without bicycle exposure.

4.6.2 Fatal and Serious Injury Crashes

4.6.2.1 Non-Signalized Intersections on State-Only Roads

Table 4.29 and Table 4.30 present the results of the Poisson models of fatal and serious injury bicycle crashes at non-signalized intersections on state-only roads, with and without bicycle exposure.

Table 4.29 Model B-NSig-KA-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-8.7870	4.3844	-2.004	0.045
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	-1.7519	1.6891	-1.037	0.300
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.3418	0.4323	0.791	0.429
Truck proportion of $AADT_{MAJ}$	-18.1028	9.2695	-1.953	0.051
Transportation characteristics				
# intersection legs or approaches	1.0059	0.3551	2.832	0.005
Land use and built-environment characteristics				
Sociodemographic characteristics				
Model fit statistics				
Sample size (N)	1695			
Log-likelihood, fitted model	-25.90			
Log-likelihood, intercept-only (null) model	-34.13			
McFadden pseudo R^2 value	0.241			

[a] The natural log of these variables (+1) entered the model.

Model name: B = bicycle, NSig = non-signalized intersections, KA = fatal and serious injury crashes, A = state-only roads with bicycle exposure.

Table 4.30 Model B-NSig-KA-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-22.0253	5.6438	-3.903	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	1.4898	0.5769	2.582	0.010
Transportation characteristics				
# intersection legs or approaches	1.2727	0.3432	3.708	<0.001
Median width (ft), major direction	-0.1532	0.0840	-1.825	0.068
Percentage grade (maximum of legs)	-0.8355	0.4633	-1.803	0.071
Land use and built-environment characteristics				
Sociodemographic characteristics				
Model fit statistics				
Sample size (N)	3175			
Log-likelihood, fitted model	-30.95			
Log-likelihood, intercept-only (null) model	-43.63			
McFadden pseudo R^2 value	0.291			

[a] The natural log of these variables (+1) entered the model.

Model name: B = bicycle, NSig = non-signalized intersections, KA = fatal and serious injury crashes, B = state-only roads without bicycle exposure.

4.6.2.2 Non-Signalized Intersections on State and Federal-Aid Roads

Table 4.31 and Table 4.32 present the results of the Poisson models of fatal and serious injury bicycle crashes at non-signalized intersections on state and federal-aid roads, with and without bicycle exposure.

Table 4.31 Model B-NSig-KA-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-13.3180	0.9584	-13.895	<0.001
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	0.2077	0.1074	1.933	0.053
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.3941	0.0826	4.772	<0.001
Transportation characteristics				
# intersection legs or approaches	1.0260	0.1260	8.142	<0.001
# of bus stops	0.4672	0.1412	3.309	0.001
Land use and built-environment characteristics				
Sociodemographic characteristics				
Household income (median, $1,000)	0.0107	0.0039	2.748	0.006
% zero-vehicle households	0.0688	0.0162	4.254	<0.001
Model fit statistics				
Sample size (N)	20793			
Log-likelihood, fitted model	-597.53			
Log-likelihood, intercept-only (null) model	-660.28			
McFadden pseudo R^2 value	0.095			

[a] The natural log of these variables (+1) entered the model.
Model name: B = bicycle, NSig = non-signalized intersections, KA = fatal and serious injury crashes, C = state and federal aid roads with bicycle exposure.

Table 4.32 Model B-NSig-KA-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-13.6663	1.0549	-12.956	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.3920	0.0765	5.127	<0.001
Transportation characteristics				
# intersection legs or approaches	0.9471	0.1110	8.531	<0.001
Presence of a bike lane	0.4292	0.2130	2.016	0.044
Distance (km) to nearest signal	-0.1288	0.0533	-2.418	0.016
# of bus stops	0.2918	0.1373	2.126	0.034
Land use and built-environment characteristics				
Residential density (housing units / acre)	0.1347	0.0587	2.294	0.022
Sociodemographic characteristics				
Household income (median, $1,000)	0.0085	0.0038	2.230	0.026
% zero-vehicle households	0.0522	0.0167	3.128	0.002
% population with a disability	0.0286	0.0120	2.385	0.017
Model fit statistics				
Sample size (N)	35787			
Log-likelihood, fitted model	-798.62			
Log-likelihood, intercept-only (null) model	-916.12			
McFadden pseudo R^2 value	0.128			

[a] The natural log of these variables (+1) entered the model.
Model name: B = bicycle, NSig = non-signalized intersections, KA = fatal and serious injury crashes, D = state and federal aid roads without bicycle exposure.

4.7 Pedestrian Crashes at Signalized Intersections

4.7.1 All Crashes

4.7.1.1 Signalized Intersections with Minor AADT

Table 4.33 and Table 4.34 present the results of the NB models of all pedestrian crashes at signalized intersections with minor AADT, with and without pedestrian exposure.

Table 4.33 Model P-Sig-All-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	3.3450	0.4410	7.59	<0.001
(Intercept)	-8.4308	0.7236	-11.651	<0.001
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.4930	0.0391	12.608	<0.001
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4837	0.0660	7.328	<0.001
Annual average daily traffic, minor direction ($AADT_{MIN}$)	0.0596	0.0203	2.931	0.003
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-1.0692	0.8090	-1.322	0.186
3-leg	-0.1150	0.1570	-0.733	0.464
Other: 5-leg, DDI, SPUI	-0.2862	0.4286	-0.668	0.504
# approaches with no pedestrian crossing	-0.1735	0.0758	-2.289	0.022
# crosswalks with continental/ladder/zebra markings	0.0897	0.0379	2.368	0.018
# approaches with bike lanes	-0.0635	0.0301	-2.110	0.035
# of bus stops within 300 ft of intersection	0.1329	0.0302	4.403	<0.001
# approaches with near-side bus stops	-0.1343	0.0542	-2.479	0.013
Land use and built-environment characteristics [b]				
% land use, residential	0.0189	0.0033	5.692	<0.001
% land use, commercial	0.0149	0.0032	4.682	<0.001
% land use, industrial	0.0099	0.0060	1.660	0.097
% land use, vacant	0.0146	0.0055	2.634	0.008
Employment density (1,000 jobs / mi^2)	-0.0077	0.0035	-2.224	0.026
# places of worship	-0.0935	0.0402	-2.326	0.020
Sociodemographic characteristics [b]				
Household income (median, $1,000)	-0.0050	0.0023	-2.172	0.030
% population with a disability	0.0173	0.0087	1.994	0.046
% population of Hispanic or non-white race/ethnicity	0.0049	0.0028	1.723	0.085
Model fit statistics				
Sample size (N)	1040			
Log-likelihood, fitted model	-1630.67			
Log-likelihood, intercept-only (null) model	-2418.64			
McFadden pseudo R^2 value	0.326			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: P = pedestrian, Sig = signalized intersections, All = all crashes, A = state-only roads with pedestrian exposure.

Table 4.34 Model P-Sig-All-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	2.4310	0.2700	9.00	<0.001
(Intercept)	-6.5633	0.7119	-9.219	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4269	0.0663	6.440	<0.001
Annual average daily traffic, minor direction ($AADT_{MIN}$)	0.0891	0.0166	5.353	<0.001
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-0.8076	0.2802	-2.882	0.004
3-leg	-0.1774	0.1439	-1.233	0.218
Other: 5-leg, DDI, SPUI	-0.0285	0.4334	-0.066	0.948
# approaches with no pedestrian crossing	-0.3327	0.0688	-4.837	<0.001
# crosswalks with continental/ladder/zebra markings	0.1542	0.0379	4.066	<0.001
Crosswalk length (mean, ft)	0.0061	0.0019	3.167	0.002
# of bus stops within 300 ft of intersection	0.1354	0.0244	5.541	<0.001
Land use and built-environment characteristics [b]				
% land use, residential	0.0190	0.0030	6.390	<0.001
% land use, commercial	0.0213	0.0029	7.324	<0.001
% land use, vacant	0.0091	0.0054	1.683	0.092
Population density (1,000 people / mi^2)	0.0552	0.0125	4.417	<0.001
Sociodemographic characteristics [b]				
Household income (median, $1,000)	-0.0104	0.0024	-4.374	<0.001
Vehicle ownership (mean)	-0.2290	0.0855	-2.680	0.007
Household size (mean)	0.1167	0.0426	2.738	0.006
% population with a disability	0.0249	0.0100	2.492	0.013
% population of Hispanic or non-white race/ethnicity	0.0100	0.0026	3.841	<0.001
Model fit statistics				
Sample size (N)	1254			
Log-likelihood, fitted model	-1916.60			
Log-likelihood, intercept-only (null) model	-2776.50			
McFadden pseudo R^2 value	0.310			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: P = pedestrian, Sig = signalized intersections, All = all crashes, B = state-only roads without pedestrian exposure.

4.7.1.2 Signalized Intersections without Minor AADT

Table 4.35 and Table 4.36 present the results of the NB models of all pedestrian crashes at signalized intersections without minor AADT, with and without pedestrian exposure.

Table 4.35 Model P-Sig-All-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	3.2390	0.3770	8.59	<0.001
(Intercept)	-7.7563	0.5985	-12.960	<0.001
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.5273	0.0332	15.879	<0.001
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4083	0.0562	7.268	<0.001
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-1.5898	0.7855	-2.024	0.043
3-leg	-0.1594	0.1250	-1.275	0.202
Other: 5-leg, DDI, SPUI	0.2345	0.2772	0.846	0.398
# approaches with no pedestrian crossing	-0.1202	0.0589	-2.040	0.041
# crosswalks with continental/ladder/zebra markings	0.0955	0.0354	2.695	0.007
Crosswalk length (mean, ft)	0.0049	0.0017	2.896	0.004
# approaches with bike lanes	-0.0577	0.0268	-2.156	0.031
# of bus stops within 300 ft of intersection	0.1434	0.0280	5.121	<0.001
# approaches with near-side bus stops	-0.1184	0.0501	-2.365	0.018
Land use and built-environment characteristics [b]				
% land use, residential	0.0212	0.0027	7.727	<0.001
% land use, commercial	0.0153	0.0026	5.962	<0.001
% land use, industrial	0.0161	0.0046	3.532	<0.001
% land use, vacant	0.0173	0.0046	3.776	<0.001
Employment density (1,000 jobs / mi^2)	-0.0074	0.0031	-2.389	0.017
# schools	-0.0800	0.0438	-1.827	0.068
# places of worship	-0.1015	0.0353	-2.872	0.004
Sociodemographic characteristics [b]				
Household income (median, $1,000)	-0.0072	0.0019	-3.729	<0.001
% population with a disability	0.0241	0.0074	3.268	0.001
Model fit statistics				
Sample size (N)	1440			
Log-likelihood, fitted model	-2176.39			
Log-likelihood, intercept-only (null) model	-3152.01			
McFadden pseudo R^2 value	0.310			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: P = pedestrian, Sig = signalized intersections, All = all crashes, C = state and federal aid roads with pedestrian exposure.

Table 4.36 Model P-Sig-All-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	2.1190	0.1990	10.65	<0.001
(Intercept)	-4.9272	0.5443	-9.052	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.3693	0.0531	6.958	<0.001
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-1.4884	0.2510	-5.931	<0.001
3-leg	-0.3792	0.1163	-3.260	0.001
Other: 5-leg, DDI, SPUI	0.6428	0.2773	2.318	0.020
# approaches with no pedestrian crossing	-0.3534	0.0552	-6.403	<0.001
# crosswalks with continental/ladder/zebra markings	0.1719	0.0357	4.810	<0.001
Crosswalk length (mean, ft)	0.0095	0.0017	5.642	<0.001
# of bus stops within 300 ft of intersection	0.1598	0.0229	6.983	<0.001
Land use and built-environment characteristics [b]				
% land use, residential	0.0148	0.0024	6.109	<0.001
% land use, commercial	0.0173	0.0024	7.295	<0.001
Population density (1,000 people / mi^2)	0.0610	0.0114	5.366	<0.001
# places of worship	-0.0819	0.0369	-2.217	0.027
Sociodemographic characteristics [b]				
Household income (median, $1,000)	-0.0109	0.0022	-5.062	<0.001
Vehicle ownership (mean)	-0.2038	0.0750	-2.716	0.007
% population with a disability	0.0247	0.0082	3.007	0.003
% population of Hispanic or non-white race/ethnicity	0.0094	0.0022	4.249	<0.001
Model fit statistics				
Sample size (N)	1740			
Log-likelihood, fitted model	-2584.31			
Log-likelihood, intercept-only (null) model	-3630.07			
McFadden pseudo R^2 value	0.288			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: P = pedestrian, Sig = signalized intersections, All = all crashes, D = state and federal aid roads without pedestrian exposure.

4.7.2 Fatal and Serious Injury Crashes

4.7.2.1 Signalized Intersections with Minor AADT

Table 4.37 and Table 4.38 present the results of the NB models of fatal and serious injury pedestrian crashes at signalized intersections with minor AADT, with and without pedestrian exposure.

Table 4.37 Model P-Sig-KA-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-12.2646	1.5200	-8.069	<0.001
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.3867	0.0658	5.880	<0.001
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.7371	0.1427	5.164	<0.001
Annual average daily traffic, minor direction ($AADT_{MIN}$)	0.0804	0.0446	1.802	0.072
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	0.5531	1.0856	0.510	0.610
3-leg	0.0763	0.2922	0.261	0.794
Other: 5-leg, DDI, SPUI	0.0477	0.6066	0.079	0.937
# of bus stops within 300 ft of intersection	0.2022	0.0536	3.774	<0.001
# approaches with near-side bus stops	-0.3225	0.1032	-3.126	0.002
Land use and built-environment characteristics [b]				
% land use, residential	0.0209	0.0058	3.585	<0.001
% land use, commercial	0.0159	0.0059	2.704	0.007
% land use, industrial	0.0215	0.0097	2.210	0.027
Sociodemographic characteristics [b]				
Household income (median, $1,000)	-0.0104	0.0041	-2.541	0.011
Model fit statistics				
Sample size (N)	1041			
Log-likelihood, fitted model	-575.79			
Log-likelihood, intercept-only (null) model	-680.11			
McFadden pseudo R^2 value	0.153			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: P = pedestrian, Sig = signalized intersections, KA = fatal and serious injury crashes, A = state-only roads with pedestrian exposure.

Table 4.38 Model P-Sig-KA-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-7.9582	1.3029	-6.108	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4897	0.1363	3.593	<0.001
Annual average daily traffic, minor direction ($AADT_{MIN}$)	0.0775	0.0324	2.390	0.017
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-0.3674	0.5697	-0.645	0.519
3-leg	-0.1692	0.2663	-0.635	0.525
Other: 5-leg, DDI, SPUI	0.0883	0.6043	0.146	0.884
Crosswalk length (mean, ft)	0.0080	0.0035	2.291	0.022
# of bus stops within 300 ft of intersection	0.2261	0.0519	4.361	<0.001
# approaches with near-side bus stops	-0.2648	0.1013	-2.614	0.009
Land use and built-environment characteristics [b]				
% land use, residential	0.0160	0.0052	3.071	0.002
% land use, commercial	0.0144	0.0053	2.723	0.006
Population density (1,000 people / mi^2)	0.0577	0.0204	2.829	0.005
Sociodemographic characteristics [b]				
Household income (median, $1,000)	-0.0123	0.0042	-2.916	0.004
Vehicle ownership (mean)	-0.3479	0.1592	-2.185	0.029
% population of Hispanic or non-white race/ethnicity	0.0086	0.0046	1.867	0.062
Model fit statistics				
Sample size (N)	1254			
Log-likelihood, fitted model	-667.40			
Log-likelihood, intercept-only (null) model	-770.16			
McFadden pseudo R^2 value	0.133			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: P = pedestrian, Sig = signalized intersections, KA = fatal and serious injury crashes, B = state-only roads without pedestrian exposure.

4.7.2.2 Signalized Intersections without Minor AADT

Table 4.39 and Table 4.40 present the results of the NB models of fatal and serious injury pedestrian crashes at signalized intersections without minor AADT, with and without pedestrian exposure.

Table 4.39 Model P-Sig-KA-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-10.7871	1.2663	-8.518	<0.001
Measures of exposure [a]				
Annual average daily pedestrian volume (AADP)	0.4267	0.0592	7.209	<0.001
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.6365	0.1167	5.452	<0.001
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-0.2027	1.0051	-0.202	0.840
3-leg	0.1652	0.2494	0.662	0.508
Other: 5-leg, DDI, SPUI	0.3629	0.5847	0.621	0.535
# approaches with no pedestrian crossing	-0.2703	0.1426	-1.895	0.058
# of bus stops within 300 ft of intersection	0.2006	0.0512	3.922	<0.001
# approaches with near-side bus stops	-0.3459	0.0985	-3.511	<0.001
Land use and built-environment characteristics [b]				
% land use, residential	0.0217	0.0052	4.157	<0.001
% land use, commercial	0.0170	0.0051	3.357	0.001
% land use, industrial	0.0221	0.0090	2.455	0.014
# schools	-0.1803	0.0932	-1.935	0.053
Sociodemographic characteristics [b]				
Household income (median, $1,000)	-0.0098	0.0037	-2.673	0.008
Model fit statistics				
Sample size (N)	1449			
Log-likelihood, fitted model	-749.11			
Log-likelihood, intercept-only (null) model	-875.84			
McFadden pseudo R^2 value	0.145			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: P = pedestrian, Sig = signalized intersections, KA = fatal and serious injury crashes, C = state and federal aid roads with pedestrian exposure.

Table 4.40 Model P-Sig-KA-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-7.2045	1.0859	-6.634	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4637	0.1134	4.087	<0.001
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-0.9195	0.5063	-1.816	0.069
3-leg	-0.1201	0.2349	-0.511	0.609
Other: 5-leg, DDI, SPUI	0.7963	0.5686	1.401	0.161
# approaches with no pedestrian crossing	-0.3927	0.1262	-3.112	0.002
Crosswalk length (mean, ft)	0.0093	0.0032	2.934	0.003
# of bus stops within 300 ft of intersection	0.2254	0.0493	4.573	<0.001
# approaches with near-side bus stops	-0.2919	0.0964	-3.029	0.002
Land use and built-environment characteristics [b]				
% land use, residential	0.0229	0.0051	4.514	<0.001
% land use, commercial	0.0214	0.0053	4.076	<0.001
% land use, industrial	0.0164	0.0090	1.830	0.067
Population density (1,000 people / mi^2)	0.0464	0.0185	2.500	0.012
Sociodemographic characteristics [b]				
Household income (median, $1,000)	-0.0166	0.0037	-4.474	<0.001
Vehicle ownership (mean)	-0.3149	0.1449	-2.173	0.030
Model fit statistics				
Sample size (N)	1737			
Log-likelihood, fitted model	-865.63			
Log-likelihood, intercept-only (null) model	-988.40			
McFadden pseudo R^2 value	0.124			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: P = pedestrian, Sig = signalized intersections, KA = fatal and serious injury crashes, D = state and federal aid roads without pedestrian exposure.

4.8 Bicycle Crashes at Signalized Intersections

4.8.1 All Crashes

4.8.1.1 Signalized Intersections with Minor AADT

Table 4.41 and Table 4.42 present the results of the NB models of all bicycle crashes at signalized intersections with minor AADT, with and without bicycle exposure.

Table 4.41 Model B-Sig-All-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	2.5070	0.3290	7.62	<0.001
(Intercept)	-6.7766	0.6708	-10.102	<0.001
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	0.1757	0.0469	3.750	<0.001
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4640	0.0701	6.618	<0.001
Annual average daily traffic, minor direction ($AADT_{MIN}$)	0.0663	0.0177	3.749	<0.001
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-1.5746	0.3951	-3.985	<0.001
3-leg	-0.3871	0.1481	-2.614	0.009
Other: 5-leg, DDI, SPUI	0.7603	0.4049	1.878	0.060
# approaches with no pedestrian crossing	-0.1332	0.0631	-2.112	0.035
Crosswalk length (mean, ft)	0.0069	0.0020	3.524	<0.001
# approaches with channelized right turns	-0.2515	0.0816	-3.081	0.002
# of bus stops within 300 ft of intersection	0.1072	0.0324	3.304	0.001
# approaches with near-side bus stops	-0.1063	0.0609	-1.747	0.081
Land use and built-environment characteristics [b]				
% land use, commercial	0.0036	0.0018	2.003	0.045
Population density (1,000 people / mi^2)	0.0842	0.0117	7.218	<0.001
# places of worship	-0.1008	0.0438	-2.301	0.021
Sociodemographic characteristics [b]				
% population with a disability	0.0271	0.0086	3.145	0.002
% population of Hispanic or non-white race/ethnicity	0.0119	0.0026	4.558	<0.001
Model fit statistics				
Sample size (N)	1244			
Log-likelihood, fitted model	-1773.94			
Log-likelihood, intercept-only (null) model	-2239.47			
McFadden pseudo R^2 value	0.208			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: B = bicycle, Sig = signalized intersections, All = all crashes, A = state-only roads with bicycle exposure.

Table 4.42 Model B-Sig-All-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	2.4730	0.3230	7.66	<0.001
(Intercept)	-6.3426	0.6479	-9.790	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4485	0.0693	6.475	<0.001
Annual average daily traffic, minor direction ($AADT_{MIN}$)	0.0810	0.0171	4.727	<0.001
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-1.4054	0.3716	-3.782	<0.001
3-leg	-0.3623	0.1481	-2.446	0.014
Other: 5-leg, DDI, SPUI	0.3825	0.3960	0.966	0.334
# approaches with no pedestrian crossing	-0.1395	0.0633	-2.204	0.027
Crosswalk length (mean, ft)	0.0062	0.0020	3.172	0.002
# approaches with channelized right turns	-0.2132	0.0798	-2.670	0.008
# approaches with bike lanes	0.0641	0.0284	2.261	0.024
# of bus stops within 300 ft of intersection	0.1110	0.0325	3.414	0.001
# approaches with near-side bus stops	-0.1122	0.0610	-1.838	0.066
Land use and built-environment characteristics [b]				
% land use, commercial	0.0035	0.0018	1.939	0.052
Population density (1,000 people / mi^2)	0.0845	0.0117	7.213	<0.001
# places of worship	-0.0898	0.0437	-2.056	0.040
Sociodemographic characteristics [b]				
% population with a disability	0.0244	0.0086	2.836	0.005
% population of Hispanic or non-white race/ethnicity	0.0089	0.0025	3.526	<0.001
Model fit statistics				
Sample size (N)	1263			
Log-likelihood, fitted model	-1798.27			
Log-likelihood, intercept-only (null) model	-2270.58			
McFadden pseudo R^2 value	0.208			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: B = bicycle, Sig = signalized intersections, All = all crashes, B = state-only roads without bicycle exposure.

4.8.1.2 Signalized Intersections without Minor AADT

Table 4.43 and Table 4.44 present the results of the NB models of all bicycle crashes at signalized intersections without minor AADT, with and without bicycle exposure.

Table 4.43 Model B-Sig-All-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	2.2040	0.2410	9.15	<0.001
(Intercept)	-6.5822	0.5931	-11.098	<0.001
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	0.2376	0.0415	5.730	<0.001
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.5200	0.0582	8.941	<0.001
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-2.0148	0.3702	-5.443	<0.001
3-leg	-0.4336	0.1160	-3.739	<0.001
Other: 5-leg, DDI, SPUI	0.5870	0.3318	1.769	0.077
# approaches with no pedestrian crossing	-0.1305	0.0502	-2.600	0.009
Crosswalk length (mean, ft)	0.0097	0.0016	5.916	<0.001
# approaches with channelized right turns	-0.1986	0.0706	-2.815	0.005
# of bus stops within 300 ft of intersection	0.1156	0.0306	3.772	<0.001
# approaches with near-side bus stops	-0.0942	0.0568	-1.659	0.097
Land use and built-environment characteristics [b]				
Population density (1,000 people / mi^2)	0.0650	0.0112	5.806	<0.001
# places of worship	-0.0924	0.0390	-2.370	0.018
Sociodemographic characteristics [b]				
Household income (median, $1,000)	-0.0061	0.0019	-3.261	0.001
% population with a disability	0.0258	0.0082	3.154	0.002
% population of Hispanic or non-white race/ethnicity	0.0105	0.0023	4.648	<0.001
Model fit statistics				
Sample size (N)	1731			
Log-likelihood, fitted model	-2393.96			
Log-likelihood, intercept-only (null) model	-2974.84			
McFadden pseudo R^2 value	0.195			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: B = bicycle, Sig = signalized intersections, All = all crashes, C = state and federal aid roads with bicycle exposure.

Table 4.44 Model B-Sig-All-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	2.1250	0.2280	9.32	<0.001
(Intercept)	-6.0877	0.5743	-10.599	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4947	0.0573	8.635	<0.001
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block)	-1.9755	0.3488	-5.663	<0.001
3-leg	-0.4494	0.1171	-3.836	<0.001
Other: 5-leg, DDI, SPUI	0.2283	0.3263	0.700	0.484
# approaches with no pedestrian crossing	-0.1582	0.0505	-3.130	0.002
Crosswalk length (mean, ft)	0.0093	0.0017	5.635	<0.001
# approaches with channelized right turns	-0.1488	0.0692	-2.149	0.032
# approaches with bike lanes	0.0820	0.0266	3.078	0.002
# of bus stops within 300 ft of intersection	0.1248	0.0308	4.046	<0.001
# approaches with near-side bus stops	-0.1039	0.0573	-1.814	0.070
Land use and built-environment characteristics [b]				
Population density (1,000 people / mi^2)	0.0707	0.0113	6.230	<0.001
Employment density (1,000 jobs / mi^2)	0.0037	0.0023	1.628	0.104
# places of worship	-0.0783	0.0390	-2.009	0.045
Sociodemographic characteristics [b]				
Household income (median, $1,000)	-0.0040	0.0019	-2.138	0.033
% population with a disability	0.0262	0.0083	3.146	0.002
% population of Hispanic or non-white race/ethnicity	0.0076	0.0023	3.330	0.001
Model fit statistics				
Sample size (N)	1750			
Log-likelihood, fitted model	-2425.91			
Log-likelihood, intercept-only (null) model	-3005.98			
McFadden pseudo R^2 value	0.193			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: B = bicycle, Sig = signalized intersections, All = all crashes, D = state and federal aid roads without bicycle exposure.

4.8.2 Fatal and Serious Injury Crashes

4.8.2.1 Signalized Intersections with Minor AADT

Table 4.45 and Table 4.46 present the results of the NB models of fatal and serious injury bicycle crashes at signalized intersections with minor AADT, with and without bicycle exposure.

Table 4.45 Model B-Sig-KA-A

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-9.5495	1.9669	-4.855	<0.001
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	0.3524	0.1239	2.843	0.004
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.4155	0.2076	2.001	0.045
Annual average daily traffic, minor direction ($AADT_{MIN}$)	0.0408	0.0514	0.793	0.428
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block) or 3-leg	-0.9192	0.5007	-1.836	0.066
Other: 5-leg, DDI, SPUI	0.4054	1.0345	0.392	0.695
Crosswalk length (mean, ft)	0.0170	0.0049	3.491	<0.001
# of bus stops within 300 ft of intersection	0.2306	0.0653	3.530	<0.001
Absence of overhead street lighting	1.1727	0.4304	2.725	0.006
Land use and built-environment characteristics [b]				
Population density (1,000 people / mi^2)	0.0635	0.0294	2.160	0.031
Sociodemographic characteristics [b]				
Model fit statistics				
Sample size (N)	1244			
Log-likelihood, fitted model	-375.73			
Log-likelihood, intercept-only (null) model	-416.74			
McFadden pseudo R^2 value	0.098			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: B = bicycle, Sig = signalized intersections, KA = fatal and serious injury crashes, A = state-only roads with bicycle exposure.

Table 4.46 Model B-Sig-KA-B

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.0000			
(Intercept)	-7.8177	1.9331	-4.044	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.3938	0.2031	1.939	0.052
Annual average daily traffic, minor direction ($AADT_{MIN}$)	0.0624	0.0499	1.251	0.211
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block) or 3-leg	-0.8072	0.4917	-1.642	0.101
Other: 5-leg, DDI, SPUI	0.0589	1.0323	0.057	0.954
Crosswalk length (mean, ft)	0.0154	0.0048	3.179	0.001
# approaches with bike lanes	0.1354	0.0726	1.866	0.062
# of bus stops within 300 ft of intersection	0.2509	0.0636	3.944	<0.001
Absence of overhead street lighting	1.0096	0.4258	2.371	0.018
Land use and built-environment characteristics [b]				
Sociodemographic characteristics [b]				
Vehicle ownership (mean)	-0.4148	0.2123	-1.954	0.051
Model fit statistics				
Sample size (N)	1255			
Log-likelihood, fitted model	-381.11			
Log-likelihood, intercept-only (null) model	-420.14			
McFadden pseudo R^2 value	0.093			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: B = bicycle, Sig = signalized intersections, KA = fatal and serious injury crashes, B = state-only roads without bicycle exposure.

4.8.2.2 Signalized Intersections without Minor AADT

Table 4.47 and Table 4.48 present the results of the NB models of fatal and serious injury bicycle crashes at signalized intersections without minor AADT, with and without bicycle exposure.

Table 4.47 Model B-Sig-KA-C

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.7100	1.1400	1.50	0.130
(Intercept)	-8.7475	1.6372	-5.343	<0.001
Measures of exposure [a]				
Annual average daily bicycle volume (Strava)	0.3119	0.1153	2.705	0.007
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.2854	0.1674	1.705	0.088
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block) or 3-leg	-0.4940	0.3237	-1.526	0.127
Other: 5-leg, DDI, SPUI	-0.2317	1.0763	-0.215	0.830
Crosswalk length (mean, ft)	0.0205	0.0043	4.721	<0.001
# of bus stops within 300 ft of intersection	0.1737	0.0632	2.748	0.006
Land use and built-environment characteristics [b]				
Population density (1,000 people / mi^2)	0.0839	0.0260	3.225	0.001
Sociodemographic characteristics [b]				
% population with a disability	0.0354	0.0197	1.797	0.072
% population of Hispanic or non-white race/ethnicity	0.0140	0.0059	2.363	0.018
Model fit statistics				
Sample size (N)	1732			
Log-likelihood, fitted model	-504.69			
Log-likelihood, intercept-only (null) model	-551.02			
McFadden pseudo R^2 value	0.084			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: B = bicycle, Sig = signalized intersections, KA = fatal and serious injury crashes, C = state and federal aid roads with bicycle exposure.

Table 4.48 Model B-Sig-KA-D

Variables	*B*	*SE*	*z*	*p*
Dispersion parameter (Theta)	1.7300	1.1700	1.48	0.134
(Intercept)	-6.5723	1.5053	-4.366	<0.001
Measures of exposure [a]				
Annual average daily traffic, major direction ($AADT_{MAJ}$)	0.2301	0.1583	1.454	0.146
Transportation characteristics				
Intersection type (ref. = 4-leg)				
2-leg (mid-block) or 3-leg	-0.6023	0.3291	-1.830	0.067
Other: 5-leg, DDI, SPUI	-0.4686	1.0733	-0.437	0.662
Crosswalk length (mean, ft)	0.0234	0.0045	5.234	<0.001
# of bus stops within 300 ft of intersection	0.1745	0.0638	2.734	0.006
Absence of overhead street lighting	0.6778	0.3930	1.725	0.085
Land use and built-environment characteristics [b]				
% land use, residential	0.0072	0.0041	1.746	0.081
Population density (1,000 people / mi^2)	0.0715	0.0266	2.691	0.007
Sociodemographic characteristics [b]				
Vehicle ownership (mean)	-0.5261	0.2022	-2.602	0.009
Model fit statistics				
Sample size (N)	1741			
Log-likelihood, fitted model	-509.29			
Log-likelihood, intercept-only (null) model	-554.23			
McFadden pseudo R^2 value	0.081			

[a] The natural log of these variables (+1) entered the model.
[b] These variables were measured using a quarter-mile network buffer.
Model name: B = bicycle, Sig = signalized intersections, KA = fatal and serious injury crashes, D = state and federal aid roads without bicycle exposure.

4.9 Comparison and Summary of Results

Given the large number of different models (48) presented in this chapter, it is instructive to summarize and compare the results across all models. First, the goodness-of-fit statistics for all of the models are presented and discussed. Then, the factors (independent variables) that were (statistically) significantly associated with pedestrian and bicycle crashes at each study location type are summarized and discussed.

4.9.1 Model Goodness of Fit

Table 4.49 and Table 4.50 summarize the sample sizes and goodness-of-fit statistics for all of the models of pedestrian and bicycle crashes, respectively. The goodness-of-fit measure was McFadden's pseudo-R^2 value, a measure of the proportion of the null (intercept-only Poisson) model log-likelihood reduced by the independent variables in the estimated model. It is a measure of the degree to which the independent variables and estimated coefficients can collectively account for the observed variations in the dependent variable from place to place. Better pseudo-R^2 values are closer to 1, while worse values are closer to 0; however, the threshold for a "good" model fit is arbitrary and differs by field and the phenomenon being modeled. Because crashes (especially pedestrian and bicycle crashes) are rare events, pseudo-R^2 values in the range of 0.05 to 0.50 are typical.

Table 4.49 Goodness of Fit for Models of Pedestrian Crashes

Location type	*Crash type*	*Model*	*N*	*Pseudo R^2*
Segments or mid-block locations	All	P-Seg-All-A	5209	0.202
		P-Seg-All-B	12638	0.220
		P-Seg-All-C	20928	0.202
		P-Seg-All-D	34094	0.198
	Fatal and serious injury	P-Seg-KA-A	5209	0.151
		P-Seg-KA-B	11723	0.207
		P-Seg-KA-C	21673	0.166
		P-Seg-KA-D	36173	0.174
Non-signalized intersections	All	P-NSig-All-A	1072	0.203
		P-NSig-All-B	3045	0.345
		P-NSig-All-C	18983	0.164
		P-NSig-All-D	35787	0.226
	Fatal and serious injury	P-NSig-KA-A	1147	0.197
		P-NSig-KA-B	3359	0.264
		P-NSig-KA-C	18983	0.092
		P-NSig-KA-D	35787	0.149
Signalized intersections	All	P-Sig-All-A	1040	0.326
		P-Sig-All-B	1254	0.310
		P-Sig-All-C	1440	0.310
		P-Sig-All-D	1740	0.288
	Fatal and serious injury	P-Sig-KA-A	1041	0.153
		P-Sig-KA-B	1254	0.133
		P-Sig-KA-C	1449	0.145
		P-Sig-KA-D	1737	0.124

Table 4.50 Goodness of fit for Models of Bicycle Crashes

Location type	*Crash type*	*Model*	*N*	*Pseudo R^2*
Segments or mid-block locations	All	B-Seg-All-A	11832	0.316
		B-Seg-All-B	12578	0.311
		B-Seg-All-C	31710	0.227
		B-Seg-All-D	36173	0.226
	Fatal and serious injury	B-Seg-KA-A	11034	0.157
		B-Seg-KA-B	12578	0.160
		B-Seg-KA-C	31710	0.133
		B-Seg-KA-D	34094	0.116
Non-signalized intersections	All	B-NSig-All-A	1469	0.287
		B-NSig-All-B	3156	0.298
		B-NSig-All-C	21643	0.158
		B-NSig-All-D	35787	0.206
	Fatal and serious injury	B-NSig-KA-A	1695	0.241
		B-NSig-KA-B	3175	0.291
		B-NSig-KA-C	20793	0.095
		B-NSig-KA-D	35787	0.128
Signalized intersections	All	B-Sig-All-A	1244	0.208
		B-Sig-All-B	1263	0.208
		B-Sig-All-C	1731	0.195
		B-Sig-All-D	1750	0.193
	Fatal and serious injury	B-Sig-KA-A	1244	0.098
		B-Sig-KA-B	1255	0.093
		B-Sig-KA-C	1732	0.084
		B-Sig-KA-D	1741	0.081

Overall, all of the goodness-of-fit statistics were fairly low (usually between 0.1 and 0.3), reflecting the difficulty of predicting when, where, and how many pedestrian and bicycle crashes occur. However, differences in goodness of fits were observed. Within each location type and crash type combination, models with smaller sample sizes (A and B) tended to have better fitting models, because more independent variables were available to explain variations in crash frequencies. Conversely, models (C and D) had larger sample sizes precisely because fewer variables were tested. Another general trend was that models of fatal and serious injury crashes had slightly worse fits than similar models of all crashes. This reflects the small crash frequencies (see Section 3.3) and the greater randomness inherent in more severe crash outcomes for people walking and bicycling.

4.9.2 Factors Associated with Pedestrian Crashes

In the following sections and tables, a + symbol means that the variable is associated with more crashes, a – symbol means that the variable is associated with fewer crashes, and a grey box means that the variable was not included in the model.

4.9.2.1 Segments or Mid-Block Locations

Table 4.51 summarizes the factors significantly associated with pedestrian crashes at segments or mid-block locations. In all cases, segments with greater pedestrian volumes and motor-vehicle traffic volumes saw more pedestrian crashes. As the percentage of trucks increased, so did pedestrian crashes.

Several roadway geometry and traffic characteristics were found to be significant predictors of pedestrian crashes in multiple models. Most notably, pedestrian crashes were higher in areas with more nearby transit stops and stations. One-way streets tended to have slightly fewer pedestrian crashes. Streets with more two-way left-turn lanes saw more pedestrian crashes, while streets with a right barrier had fewer pedestrian crashes. As driveway density increased, so did pedestrian crashes, especially for driveways to commercial and residential properties. State highways (compared to local roads) had more pedestrian crashes, but only when other roadway characteristics were not included (models C and D). Roads with higher speed limits saw fewer pedestrian crashes, but only when pedestrian exposure was not included (models B and D); this may reflect speed's negative association with pedestrian volume, rather than with crashes.

Among neighborhood and community characteristics, more pedestrian crashes were observed in neighborhoods with greater Hispanic or non-white populations and areas with more zero-vehicle households. Segments near areas with more people with a disability saw fewer pedestrian crashes, as did areas with greater employment density (but only when pedestrian volume was included). The positive association with population density only occurred when pedestrian exposure was not included (models B and D), again suggesting that this factor acts as a proxy for pedestrian volume in these situations.

Table 4.51 Factors Associated with Pedestrian Crashes at Segments or Mid-Block Locations

	P-Seg-All				*P-Seg-KA*			
Variable	***A***	***B***	***C***	***D***	***A***	***B***	***C***	***D***
Measures of exposure [a]								
Annual average daily pedestrian volume (AADP)	+		+		+		+	
Average daily traffic (AADT)	+	+	+	+	+	+	+	+
Roadway geometry and traffic characteristics								
Truck proportion of AADT	+				+	+		
Interstate, US, or Utah numbered highway			+	+			+	+
One-way road segment	–	–	–	–			–	–
Elevated road segment								
Through lane width (ft)								
# through lanes		–						
# left-turn lanes								
# right-turn lanes					–			
# two-way left-turn lanes	+	+			+			
Presence of a right shoulder					+			
Presence of an island								
Presence of a median								
Presence of rumble strips		–				–		
Presence of a right barrier	–	–			–	–		
Driveways (# / km), commercial	+	+			+	+		
Driveways (# / km), industrial	+	+						
Driveways (# / km), residential	+	+			+	+		
# bike lanes		–			–			
Percentage grade						+		
Speed limit (mi / hr)		–		–		–		–
# bus stops	+	+	+	+	+	+	+	+
# commuter rail stations (within 400 m)			+	+			+	+
# light rail stations (within 400 m)			+	+				
Neighborhood community characteristics								
Residential density (housing units / acre)		+	–	+				+
Employment density (jobs / acre)	–		–	+	–	–	–	
Jobs-housing balance (jobs / household)			–	–			–	
Household income (median, $1,000)			–	–		–		
% zero-vehicle households	+	+			+	+	+	+
% population with a disability	–	–	–		–	–	–	
% population of Hispanic or non-white race/ethnicity	+	+	+	+	+	+	+	+

[a] The natural log of these variables (+1) entered the model.

4.9.2.2 Non-Signalized Intersections

Table 4.52 summarizes the factors significantly associated with pedestrian crashes at non-signalized intersections. In all cases, intersections with greater pedestrian volumes saw more pedestrian crashes. While most models found that pedestrian crashes increase with higher motor-vehicle traffic volumes, some models found no significant relationship. Truck percentage was not associated with pedestrian crashes at non-signalized intersections.

A few other characteristics were significantly associated with pedestrian crashes. Most notably, pedestrian crashes were higher at non-signalized intersections with more legs or approaches: i.e., 5-legs vs. 3-legs. Intersections with more nearby bus stops also saw greater pedestrian crashes (although not in all models). Several models showed that higher speed limits were associated with fewer pedestrian crashes, but as with segments, this was mostly when pedestrian exposure was not included in the models; suggesting that speed's primary relationship is with volume rather than crashes. Some models indicated that more pedestrian crashes were found in neighborhoods with lower household incomes and greater Hispanic or non-white populations, but usually only for models at state and federal-aid roads (models C and D).

Table 4.52 Factors Associated with Pedestrian Crashes at Non-Signalized Intersections

	P-NSig-All				***P-NSig-KA***			
Variable	***A***	***B***	***C***	***D***	***A***	***B***	***C***	***D***
Measures of exposure [a]								
Annual average daily pedestrian volume (AADP)	+		+		+		+	
Average daily traffic, major direction ($AADT_{MAJ}$)		+	+	+			+	+
Roadway geometry and traffic characteristics								
Truck proportion of $AADT_{MAJ}$								
# intersection legs or approaches	+	+	+	+	+	+	+	+
Through lane width (ft), major direction								
# through lanes, major direction	–							
# left-turn lanes, major direction								
# right-turn lanes, major direction								
Shoulder width (ft), major direction		+						
Median width (ft), major direction								
Presence of a bike lane			–	–				
Percentage grade (maximum of legs)								
Speed limit (mi / hr) (maximum of legs)	–	–		–		–		–
Distance (km) to nearest intersection				–				–
Distance (km) to nearest signal								–
# bus stops			+	+		+	+	+
# commuter rail stations (within 400 m)				+				
# light rail stations (within 400 m)								
Neighborhood community characteristics								
Residential density (housing units / acre)		+		+				
Employment density (jobs / acre)			–				–	
Jobs-housing balance (jobs / household)								–
Household income (median, $1,000)		–	–	–			–	–
% zero-vehicle households								
% population with a disability			+	+				
% population of Hispanic or non-white race/ethnicity			+	+				+

[a] The natural log of these variables (+1) entered the model.

4.9.2.3 Signalized Intersections

Table 4.53 summarizes the factors significantly associated with pedestrian crashes at signalized intersections. In all cases, intersections with greater pedestrian volumes and motor vehicle traffic volumes (in both major and minor directions) saw more pedestrian crashes.

Several transportation characteristics were consistently found to be significant predictors of pedestrian crashes. Most notably, pedestrian crashes were higher in areas with more nearby bus stops; however, the association seemed to be more about far-side rather than near-side bus stops. Signals with longer crossing distances had more pedestrian crashes in several models, as did intersections with more high-visibility (continental, ladder, or zebra style) crosswalk markings. This finding about crosswalk type is counterintuitive: Most previous research finds that high-visibility crosswalks increase visibility and awareness and improve safety outcomes. This result may be a statistical artifact specific to this study's data and may not be reproduced in a different or future study. Signals with more crossings where pedestrians were prohibited and with mid-block signals tended to have fewer pedestrian crashes. In two models, fewer pedestrian crashes were found when more bike lanes were present.

Considering land use and built-environment characteristics, more pedestrian crashes were found when more land near the signal was for residential or commercial uses (and sometimes industrial). Areas with greater population density had more pedestrian crashes; however, this was only for models without pedestrian exposure (models B and D). Given the strong association between pedestrian volume and population density, this is likely a spurious correlation due to the missing pedestrian volume variable in these models.

Among sociodemographic characteristics, the most consistent finding was for household income: Signals in neighborhoods with lower median incomes saw more pedestrian crashes. Also, more pedestrian crashes were found in areas with greater populations with a disability and with Hispanic or non-white race/ethnicity (although not as much for fatal and serious injury crashes). The negative association with vehicle ownership, only for models without pedestrian exposure, again suggests that the relationship with vehicle ownership is more about pedestrian volume and less about pedestrian crashes.

Table 4.53 Factors Associated with Pedestrian Crashes at Signalized Intersections

	P-Sig-All				*P-Sig-KA*			
Variable	***A***	***B***	***C***	***D***	***A***	***B***	***C***	***D***
Measures of exposure [a]								
Annual average daily pedestrian volume (AADP)	+		+		+		+	
Average daily traffic, major direction ($AADT_{MAJ}$)	+	+	+	+	+	+	+	+
Average daily traffic, minor direction ($AADT_{MIN}$)	+	+			+	+		
Transportation characteristics								
Intersection type (ref. = 4-leg)								
2-leg (mid-block)		−	−	−				−
3-leg				−				
Other: 5-leg, DDI, SPUI				+				
# approaches with no pedestrian crossing	−	−	−	−			−	−
# crosswalks, continental/ladder/zebra markings	+	+	+	+				
Crosswalk length (mean, ft)		+	+	+		+		+
# approaches with no right-turn-on-red								
# approaches with channelized right turns								
# approaches with bike lanes	−		−					
# of bus stops within 300 ft of intersection	+	+	+	+	+	+	+	+
# approaches with near-side bus stops	−		−		−	−	−	−
Absence of overhead street lighting								
Land use and built-environment characteristics								
% land use, residential	+	+	+	+	+	+	+	+
% land use, commercial	+	+	+	+	+	+	+	+
% land use, industrial	+		+		+		+	+
% land use, vacant	+	+	+					
Population density (1,000 people / mi^2)		+		+		+		+
Employment density (1,000 jobs / mi^2)	−		−					
Park area (acre)								
# schools			−				−	
# places of worship	−		−	−				
Sociodemographic characteristics								
Household income (median, $1,000)	−	−	−	−	−	−	−	−
Vehicle ownership (mean)		−		−		−		−
Household size (mean)		+						
% population with a disability	+	+	+	+				
% population of Hispanic or non-white race/ethnicity	+	+		+		+		

[a] The natural log of these variables (+1) entered the model.

4.9.3 Factors Associated with Bicycle Crashes

In the following sections and tables, a + symbol means that the variable is associated with more crashes, a – symbol means that the variable is associated with fewer crashes, and a grey box means that the variable was not included in the model.

4.9.3.1 Segments or Mid-Block Locations

Table 4.54 summarizes the factors significantly associated with bicycle crashes at segments or mid-block locations. In all cases, segments with greater Strava bicycle volumes and motor-vehicle traffic volumes saw more bicycle crashes. There was no significant association with the percentage of trucks and bicycle crashes.

Several roadway geometry and traffic characteristics were found to be significant predictors of bicycle crashes in multiple models. Most notably, bicycle crashes were higher in areas with more nearby transit stops and stations. Streets with a median, rumble strips, and/or a right barrier had fewer bicycle crashes, while streets with steeper grades saw more bicycle crashes. As driveway density increased, so did bicycle crashes, especially for driveways to commercial and residential properties. State highways (compared to local roads) had more bicycle crashes and one-way streets had fewer bicycle crashes, but only when other roadway characteristics were not included (models C and D). Roads with higher speed limits saw fewer bicycle crashes in all models. However, this may be the result of a less-robust measure of bicycle exposure, since speed may be negatively associated with bicycle volume rather than crashes.

Among neighborhood and community characteristics, more bicycle crashes were observed in areas with greater employment density (but not for fatal and serious injury crashes). In a few models, segments in neighborhoods with lower household income, fewer people with a disability, and larger Hispanic or non-white populations experienced more bicycle crashes. The consistently positive association between crashes and residential density (as with speed limit) was likely a spurious positive relationship with bicycle volumes due to the use of Strava bicycle volumes (which may not reflect all bicycle trips).

Table 4.54 Factors Associated with Bicycle Crashes at Segments or Mid-Block Locations

	B-Seg-All				*B-Seg-KA*			
Variable	***A***	***B***	***C***	***D***	***A***	***B***	***C***	***D***
Measures of exposure [a]								
Annual average daily bicycle volume (Strava)	+		+		+		+	
Average daily traffic (AADT)	+	+	+	+	+	+	+	+
Roadway geometry and traffic characteristics								
Truck proportion of AADT								
Interstate, US, or Utah numbered highway			+	+			+	+
One-way road segment			−	−			−	−
Elevated road segment		−	−	−				
Through lane width (ft)	−	−			−	−		
# through lanes								
# left-turn lanes	+	+						
# right-turn lanes								
# two-way left-turn lanes								
Presence of a right shoulder								
Presence of an island								
Presence of a median	−	−				−		
Presence of rumble strips	−	−			−	−		
Presence of a right barrier	−	−				−		
Driveways (# / km), commercial	+	+			+	+		
Driveways (# / km), industrial	+	+						
Driveways (# / km), residential	+	+			+	+		
# bike lanes		+				+		
Percentage grade	+	+			+	+		
Speed limit (mi / hr)	−	−	−	−	−	−	−	−
# bus stops	+	+	+	+	+	+	+	+
# commuter rail stations (within 400 m)	+	+						
# light rail stations (within 400 m)								
Neighborhood community characteristics								
Residential density (housing units / acre)	+	+	+	+	+	+	+	+
Employment density (jobs / acre)	+	+	+	+				
Jobs-housing balance (jobs / household)								
Household income (median, $1,000)			−		−		−	+
% zero-vehicle households								
% population with a disability			−	−			−	−
% population of Hispanic or non-white race/ethnicity	+		+	+				

[a] The natural log of these variables (+1) entered the model.

4.9.3.2 Non-Signalized Intersections

Table 4.55 summarizes the factors significantly associated with bicycle crashes at non-signalized intersections. Bicycle exposure was positively associated with crashes in only one model. While most models found that bicycle crashes increase with higher motor vehicle traffic volumes, some models (A) found no significant relationship. Instead, fewer bicycle crashes were observed as the percentage of trucks increased in these models.

A few other characteristics were significantly associated with bicycle crashes. Most notably, bicycle crashes were higher at non-signalized intersections with more legs or approaches. Intersections with more nearby bus stops and with bike lanes also saw greater bicycle crashes (although mostly when other factors were absent). Bicycle crashes were also less frequent at intersections with wider medians, steeper grades, and greater distances between signals, but not consistently across models. Associations with household income and Hispanic or non-white population were not consistent across models. As with segments, the positive association of crashes with residential density and zero-vehicle households in some models was more likely an association with bicycle volume than with bicycle crashes.

Table 4.55 Factors Associated with Bicycle Crashes at Non-Signalized Intersections

	B-NSig-All				***B-NSig-KA***			
Variable	***A***	***B***	***C***	***D***	***A***	***B***	***C***	***D***
Measures of exposure [a]								
Annual average daily bicycle volume (Strava)							+	
Average daily traffic, major direction ($AADT_{MAJ}$)		+	+	+		+	+	+
Roadway geometry and traffic characteristics								
Truck proportion of $AADT_{MAJ}$	−	−			−			
# intersection legs or approaches	+	+	+	+	+	+	+	+
Through lane width (ft), major direction								
# through lanes, major direction		−						
# left-turn lanes, major direction	−							
# right-turn lanes, major direction	+							
Shoulder width (ft), major direction								
Median width (ft), major direction	−	−				−		
Presence of a bike lane			+	+				+
Percentage grade (maximum of legs)		−				−		
Speed limit (mi / hr) (maximum of legs)			−	−				
Distance (km) to nearest intersection	+			−				
Distance (km) to nearest signal	−		−	−				−
# bus stops			+	+			+	+
# commuter rail stations (within 400 m)	+	+		+				
# light rail stations (within 400 m)								
Neighborhood community characteristics								
Residential density (housing units / acre)		+	+	+				+
Employment density (jobs / acre)			+	+				
Jobs-housing balance (jobs / household)								
Household income (median, $1,000)	−			−			+	+
% zero-vehicle households		+					+	+
% population with a disability		+		+				+
% population of Hispanic or non-white race/ethnicity		−	+	+				

[a] The natural log of these variables (+1) entered the model.

4.9.3.3 Signalized Intersections

Table 4.56 summarizes the factors significantly associated with bicycle crashes at signalized intersections. In all cases, intersections with greater bicycle volumes and motor-vehicle traffic volumes (in the major direction) saw more bicycle crashes.

Several transportation characteristics were consistently found to be significant predictors of bicycle crashes. Most notably, bicycle crashes were higher in areas with more nearby bus stops; however, the association seemed to be more about far-side rather than near-side bus stops (at least for total crashes); this result was also found for pedestrian crashes. Also, signals with longer crossing distances had more bicycle crashes across all models. Compared to 4-leg intersections, signals with 3-legs and mid-block signals saw fewer bicycle crashes. For total crashes, fewer bicycle crashes were found at signals with pedestrian-prohibited crossings and with channelized right turns. Signals without overhead street lights saw more fatal and serious injury pedestrian crashes.

Considering land use and built-environment characteristics, the only consistent finding was a positive association with population density. Again, it is likely that this finding reflects the inadequacy of Strava volumes to represent all bicycle volumes, and that population density is acting as a proxy for bicycle exposure rather than necessarily being positively related to bicycle crashes. Signals near places of worship had fewer total bicycle crashes. Among sociodemographic characteristics, the only consistent finding was that bicycle crashes were more frequent for signals in neighborhoods with greater populations with a disability and with people of Hispanic or non-white race/ethnicity.

Table 4.56 Factors Associated with Bicycle Crashes at Signalized Intersections

	B-Sig-All				*B-Sig-KA*			
Variable	***A***	***B***	***C***	***D***	***A***	***B***	***C***	***D***
Measures of exposure [a]								
Annual average daily bicycle volume (Strava)	+		+		+		+	
Average daily traffic, major direction ($AADT_{MAJ}$)	+	+	+	+	+	+	+	+
Average daily traffic, minor direction ($AADT_{MIN}$)	+	+						
Transportation characteristics								
Intersection type (ref. = 4-leg)								
2-leg (mid-block)	−	−	−	−	−			−
3-leg	−	−	−	−	−			−
Other: 5-leg, DDI, SPUI	+		+					
# approaches with no pedestrian crossing	−	−	−	−				
# crosswalks, continental/ladder/zebra markings								
Crosswalk length (mean, ft)	+	+	+	+	+	+	+	+
# approaches with no right-turn-on-red								
# approaches with channelized right turns	−	−	−	−				
# approaches with bike lanes		+				+		
# of bus stops within 300 ft of intersection	+	+	+	+	+	+	+	+
# approaches with near-side bus stops	−	−	−	−				
Absence of overhead street lighting					+	+		+
Land use and built-environment characteristics								
% land use, residential								+
% land use, commercial	+	+						
% land use, industrial								
% land use, vacant								
Population density (1,000 people / mi^2)	+	+	+	+	+		+	+
Employment density (1,000 jobs / mi^2)				+				
Park area (acre)								
# schools								
# places of worship	−	−	−	−				
Sociodemographic characteristics								
Household income (median, $1,000)			−	−				
Vehicle ownership (mean)						−		−
Household size (mean)								
% population with a disability	+	+	+	+			+	
% population of Hispanic or non-white race/ethnicity	+	+	+	+			+	

[a] The natural log of these variables (+1) entered the model.

4.10 Summary

This chapter presented results of the data analysis process. First, results of 48 different Poisson and negative binomial regression models of pedestrian and bicycle crash frequencies were shown. The models accounted for different location types, modes, crash types, facility types, and levels of data availability. Next, model results were summarized by goodness of fit: Models with more variables but smaller sample sizes had better fits, in general. Finally, results were compared to identify factors associated with more or fewer pedestrian and bicycle crashes. Commonalities across all location types were that sites with more motor-vehicle traffic volumes and more pedestrian and bicycle volumes saw more pedestrian crashes, as did segments with more driveways, intersections with more legs/approaches, and all locations with more nearby transit stops. These crash frequency model results—specifically, which variables were associated with more crashes—will be useful in the following chapter when determining risk factors for pedestrian and bicycle crashes.

5.0 APPLICATION

5.1 Overview

This chapter applies the crash frequency models described in the previous chapter towards a systemic analysis of pedestrian and bicycle safety. First, using the literature review and the model results, risk factors for pedestrian and bicycle crashes are determined. Second, countermeasures that are linked to those risk factors are listed and described. Third, methods for identifying treatment locations (and countermeasures for those sites) are described. Also, an interactive interface for helping to filter and/or screen locations for treatment is presented, with an example for segments or mid-block locations.

5.2 Determination of Risk Factors

As reviewed in Sections 2.2 and 2.3, risk factors for greater numbers of pedestrian and bicycle crashes can be determined using various (or a combination of) methods (Thomas et al., 2018). The method recommended by the *Highway Safety Manual* (AASHTO, 2010) is to develop safety performance functions (SPFs)—using crash frequency models, such as negative binomial regression—using local data. These SPFs identify roadway, traffic, and other site characteristics associated with greater or fewer crashes; thus, the version or presence/absence of the variable associated with greater crashes can be considered a risk factor. Thomas et al. (2018) also mention using cross-tabulations as a less-robust but still quantitative means of identifying risk factors from types of locations with greater observed crash frequencies. Another method is to borrow risk factors from a combination of prior research and expert/local knowledge, assuming that the risk factors identified elsewhere apply to the local context.

This project relied upon both locally estimated SPFs and prior research in order to determine risk factors for pedestrian and bicycle crashes in Utah. Identified risk factors for each location type are shown in Table 5.1. Risk factors identified from the prior research literature were taken from the literature reviews of Sections 2.4 and 2.5 as well as from a recent NCHRP report on systemic pedestrian safety analysis (Thomas et al., 2018). Risk factors from the SPF models were determined using the factors associated with crashes from the model summary tables of Section 4.9.

Table 5.1 Risk Factors for Pedestrian and Bicycle Crashes

	Pedestrian crashes		*Bicycle crashes*	
Risk factor	*Literature*	*Models*	*Literature*	*Models*
Segments or mid-block locations				
Higher pedestrian volume	✓	✓		n/a
Higher bicycle volume		n/a	✓	✓
Higher motor-vehicle traffic volumes	✓	✓	✓	✓
Greater percentage of trucks	✓*	✓*		
Arterial and collector roadways (vs. local streets)	✓	✓		✓*
Two-way streets (vs. one-way streets)		✓		✓*
More travel lanes / longer crossing distances	✓			
Narrower through lane widths			✓	✓
Presence of two-way left-turn lanes	✓	✓		
Absence of a right shoulder			✓	
Absence of a median or island	✓		✓	✓
Absence of rumble strips			✓	✓
Absence of a right barrier		✓		✓
Absence of more protected bicycle lanes			✓	
Presence of on-street parking	✓	n/a		n/a
More driveways		✓	✓	✓
Steeper roadway grades	✓			✓
Higher speed limits	✓*		✓*	
More transit stops nearby	✓	✓	✓	✓
Lower employment density		✓		
More zero-vehicle households	✓	✓	✓	
More Hispanic or non-white populations	✓	✓	✓	
Non-signalized intersections				
Higher pedestrian volume	✓	✓		n/a
Higher bicycle volume		n/a	✓	
Higher motor-vehicle traffic volumes	✓	✓	✓	✓
Greater percentage of trucks	✓*			
Arterial and collector roadways (vs. local streets)	✓	n/a		n/a
More intersection legs or approaches	✓	✓	✓	✓
More travel lanes / longer crossing distances	✓			
More turning vehicles / turn lanes	✓		✓	
Absence of a median or island	✓		✓	✓
Presence of on-street parking	✓			
More driveways	✓	n/a	✓	n/a
Higher speed limits	✓*		✓*	
More transit stops nearby	✓	✓	✓	✓
Lower household incomes	✓	✓	✓	
Signalized intersections				
Higher pedestrian volume	✓	✓		n/a
Higher bicycle volume		n/a	✓	✓
Higher motor-vehicle traffic volumes	✓	✓	✓	✓
Greater percentage of trucks	✓*	n/a		n/a
Arterial and collector roadways (vs. local streets)	✓	n/a		n/a
More intersection legs or approaches	✓	✓	✓	✓
More travel lanes / longer crossing distances	✓	✓		✓
More turning vehicles / turn lanes	✓		✓	

Absence of a median or island	✓	n/a	✓	n/a
Absence of a channelized right-turn lane				✓
Presence of on-street parking	✓	n/a		n/a
More driveways	✓	n/a	✓	n/a
Higher speed limits	✓*	n/a	✓*	n/a
More transit stops nearby	✓	✓	✓	✓
Greater share of residential land uses	✓	✓		
Greater share of commercial land uses	✓	✓		
Lower household incomes	✓	✓	✓	
More people with a disability		✓		✓
More Hispanic or non-white populations	✓	✓	✓	✓

* Risk factor is associated with more severe crashes, rather than just crash frequency.
n/a = Risk factor was not available or not tested for that crash and location type combination.

Across all types of locations, sites with high motor-vehicle traffic volumes and higher pedestrian or bicycle volumes saw greater pedestrian and bicycle crashes. This makes sense, since these are all measures of exposure, meaning that there are more opportunities for conflicts and crashes to occur. Having more transit stops nearby was also a crash risk factor across all location types. Non-motorized users (especially pedestrians) concentrate around transit stops, which involve complicated stopping, turning, and crossing movements and behaviors; buses may sometimes obscure people walking and bicycling. Also, bus stops may concentrate pedestrian and bicycle volumes at specific locations in a way not fully captured by the measures of exposure.

Among sociodemographic characteristics, both the literature and the crash frequency models identified common risk factors. In general, more pedestrian and/or bicycle crashes were observed in neighborhoods with lower average household incomes and vehicle ownership, and greater shares of people with a disability and of Hispanic or non-white race/ethnicity. While some of these characteristics are associated with pedestrian and bicycle use, the results remained even when controlling for pedestrian/bicycle volumes. Thus, these findings reflect other research showing how lower income and minority neighborhoods experience a greater share of the burden of road traffic crashes, injuries, and fatalities, especially for pedestrians (Roll & McNeil, 2021). This is related to the suburbanization of poverty in areas and along larger, higher-speed roadways with fewer safe walking, crossing, and bicycling facilities (Schneider et al., 2021).

Some risk factors were specific to segments or mid-block locations. Roadways with more driveways and higher functional classes (not local) generally saw more pedestrian and bicycle crashes. Driveways introduce greater conflicts between turning motor vehicles and people walking and bicycling and more chances for crashes to occur. Similarly, the presence of a two-way left-turn (TWLTL) lane was a risk factor for pedestrian crashes. Perhaps this is because TWLTLs are common to wider streets with more driveways and left-turning vehicles, where drivers may be less attentive to pedestrians crossing or on the sidewalk, or pedestrians may be induced to crossing, thinking that TWLTLs provide more protection than they actually do. Bicycle risk factors on segments included narrow lanes and the absence of medians and rumble strips. In places without bicycle lanes, narrow lanes may force people bicycling to share the road, sometimes with much higher-speed motor vehicles. Medians help manage access and reduce turning conflicts, while rumble strips on non-urban highways can help warn drivers that they are entering shoulders where people bicycling may be present. A few segment risk factors were identified in the models but not in the literature review: On average, there were fewer pedestrian/bicycle crashes on one-way streets and on highways with a right-side barrier. One-way streets can reduce turning conflicts, while barriers might reduce run-off-the-road crashes. While the models (and the literature) found truck percentage to be a risk factor for severe pedestrian crashes, speed limit (a similar risk factor for severe crashes) was not identified using the crash models. As mentioned in previous literature, this may be due to avoidance behaviors, where many people walking/bicycling avoid or are more cautious around high-speed roadways.

Fewer common risk factors were identified for non-signalized intersections, which may reflect the lower pedestrian and bicycle crash frequencies found at these locations compared to other location types (see Section 3.3). The most consistent risk factor (across the literature and the models) was that intersections with more legs or approaches saw more crashes. This is likely related to intersection complexity, turning movements, and exposure. Motor vehicle drivers may be less able to attend to people walking and bicycling because of the complexity of the intersection, while people walking and bicycling may have to spend more time crossing multiple legs and being exposed to through-moving or turning traffic. The absence of a median was also a risk factor for bicycle crashes, for the same reasons as was mentioned for segments. Although the literature suggested other risk factors such as through lanes or crossing distances, turn lanes or turning traffic, on-street parking, and speed limit and truck percentage (more for severe crashes), the models did not identify similar factors or data were not available to test some of these factors.

Similarly, the literature and models identified additional risk factors for signalized intersections. Having more legs or approaches was a risk factor for pedestrian and bicycle crashes, for the same reasons as was mentioned for non-signalized intersections. Crossing distance was also a risk factor for both pedestrian and bicycle crashes; this is likely related to greater time spent being exposed to traffic while crossing. Although it wasn't found in the literature search, signals with channelized right-turns had fewer bicycle crashes; this could be related to simplifying conflicts with right-turning vehicles from a turn at the intersection to a merge prior to the intersection. Other signalized intersection risk factors identified in the literature—increased truck percentage, more turn lanes or higher turning volumes, absence of a median or island, presence of parking, greater number of driveways, and higher speed limits—were either not corroborated or were not available to be tested in the crash models.

All of these risk factors identified are plausible: The relationship with pedestrian/bicycle safety makes sense, with a logical causal linkage with crash occurrences or severity outcomes. Many of them are also *treatable*; i.e., they have an associated countermeasure or treatment that a transportation agency can implement (usually a change in the design or operation of the roadway segment or intersection). However, some risk factors are less treatable, such as land use or neighborhood sociodemographic characteristics. These types of risk factors can be considered to be *contextual*; i.e., they can help indicate the appropriateness of countermeasures for specific types of locations. They also do explain variations in crash frequencies, which can help when prioritizing potential treatment locations. Based on these risk factors, the following sections first describe relevant and treatable countermeasures, and then present methods for selecting potential treatment sites for applying those countermeasures and with greatest potential for safety improvements.

5.3 Determination of Relevant Countermeasures

In systemic safety analysis, the typical step following the determination of risk factors is to identify potential treatment sites having these risk factors. However, Thomas et al. (2018) note that it is important to consider whether or not the risk factors are treatable using countermeasures that are effective and appropriate for the context and that are applied in a systemic way (across multiple locations, or through changes to policy or practice). Therefore, for this project, it is useful to re-arrange the steps and first consider effective systemic countermeasures that can be linked to each of the treatable risk factors identified in the previous section.

An initial procedure for this process is to develop a list of potential systemic countermeasures. Such countermeasures should be: related to mitigating a particular risk (linked to a risk factor); effective (having documented and logical safety benefits, as well as having greater benefits than costs); and feasible (something that the transportation agency is willing and able to implement). It is beyond the scope of this project to determine whether UDOT considers the countermeasures identified to be desirable or feasible to implement. Also, a cost-benefit assessment is also beyond the scope of this research. However, the following paragraphs document potential countermeasures that are linked to identified risk factors for pedestrian and bicycle crashes and that prior research has determined to be effective. Several sources were reviewed in order to determine appropriate and effective pedestrian/bicycle safety countermeasures, including recent NCHRP reports (Thomas et al., 2018; Sanders et al., 2020; Kittelson & Associates et al., 2022); the PEDSAFE and BIKESAFE resources (UNC HSRC, 2013, 2014); and FHWA resources (FHWA, 2018; Blackburn et al., 2018; Albee & Bobitz, 2021). There is more literature on pedestrian safety countermeasures than on bicycle safety countermeasures.

Table 5.2 shows the list of identified countermeasures, their considerations, and their relations to pedestrian and bicycle crash risk factors. In general, there tends to be more evidence about effectiveness for pedestrian safety countermeasures, because research on bicycle safety countermeasures is more recent and not as fully developed. Multiple countermeasures may help treat similar risks (such as regarding speeds), while a single countermeasure can mitigate multiple risk factors.

Table 5.2 Potential Countermeasures for Pedestrian and Bicycle Safety

Countermeasure	*Risk factor(s)*
All locations (segments and intersections)	
Corridor access management	
• Reduce turning conflicts and driveway density by closing, consolidating, or relocating driveways. • Manage spacing of intersections. • Consider medians, islands, and other features limiting driveway movements (e.g., right-in, right-out). • References: UNC HSRC, 2014; Albee & Bobitz, 2021	• Absence of a median or island (P/B) • More driveways (P/B) • Presence of two-way left-turn lanes (P)
Medians and pedestrian refuge islands	
• Aid pedestrians to cross one direction of traffic at a time, and manage left-turning conflicts. • Consider on urban/suburban multilane streets, especially with traffic volumes over 9,000 vehicles/day and speeds 35 mph or more. • Consider for mid-block crossings, on approaches to multilane intersections, and near transit stops. • References: UNC HSRC, 2013, 2014; Blackburn et al., 2018; FHWA, 2018; Thomas et al., 2018; Albee & Bobitz, 2021	• Higher motor-vehicle traffic volumes (P/B) • Absence of a median or island (P/B) • Presence of two-way left-turn lanes (P) • Higher speed limits (P/B) • More transit stops nearby (P/B)
Appropriate speed limits for all road users	
• In urban core areas, consider 20 mph limits "where vulnerable road users share the road with motorists" (Albee & Bobitz, 2021). • Consider land use, intersection spacing, driveway density, roadway geometry, roadside conditions, functional classifications, traffic volumes, observed speeds. • Implement alongside other speed management strategies, such as self-enforcing roadways or traffic calming. • References: Albee & Bobitz, 2021	• Higher speed limit (P/B)
High-visibility crosswalk markings	
• Increases conspicuity of the crosswalk and driver yielding. • Consider high-visibility crosswalks (i.e., continental, ladder) at "all midblock pedestrian crossings and uncontrolled intersections" (Albee & Bobitz, 2021). • Additional treatments (beyond just crosswalk markings) may be needed on higher-speed, higher-volume, and multilane roads. • References: UNC HSRC, 2013; Blackburn et al., 2018; FHWA, 2018; Thomas et al., 2018; Sanders et al., 2020; Albee & Bobitz, 2021	• More travel lanes / longer crossing distances (P/B)
Curb extensions with parking restrictions	
• Both improve pedestrian and driver visibility. Extended curbs also shorten crossing distances and (at intersections) reduce turning speeds. • Consider bicycle facility types and turning radii for large vehicles. • References: UNC HSRC, 2013; Blackburn et al., 2018; FHWA, 2018; Thomas et al., 2018; Sanders et al., 2020	• More travel lanes / longer crossing distances (P) • Presence of on-street parking (P) • Higher speed limits (P/B)
Lighting	
• Increased pedestrian visibility, especially in night or low-light conditions. • Consider continuous lighting on urban and rural highways. • Carefully place luminaries forward of crosswalks to avoid silhouettes. • References: UNC HSRC, 2013, 2014; Blackburn et al., 2018; FHWA, 2018; Thomas et al., 2018; Sanders et al., 2020; Albee & Bobitz, 2021	

Countermeasure	*Risk factor(s)*
Pedestrian hybrid beacons (PHB) • Aids in pedestrians crossing higher-speed roadways at midblock crossings or uncontrolled intersections. • Especially effective at three or more lane crossings, with traffic volumes over 9,000 vehicles/day, or with speeds above 35 mph. • References: UNC HSRC, 2013; Blackburn et al., 2018; FHWA, 2018; Thomas et al., 2018; Sanders et al., 2020; Albee & Bobitz, 2021; Kittelson & Associates et al., 2022	• Higher motor-vehicle traffic volumes (P/B) • Arterial and collector roadways (vs. local streets) (P) • More travel lanes / longer crossing distances (P) • Higher speed limits (P/B)
Grade separated crossings • Grade separation (elevated on a bridge, depressed in a tunnel) eliminates conflicts with motor vehicles. • Consider for high volumes of pedestrian and bicycle traffic, especially when people walking and bicycling are more likely to be traveling longer distances (such as on a trail) or not accessing the street being crossed. • Grade separation may increase travel time and result in out-of-direction travel, or involve accessibility challenges with stairs and ramps. • References: UNC HSRC, 2013, 2014; FHWA, 2018; Sanders et al., 2020	
Segments or mid-block locations	
Walkways • Sidewalks, shared-use paths, or other walkways should be incorporated into all roadway projects, especially in urban areas and near school zones or transit stops. • Walkable shoulders should be considered on rural highways used by pedestrians. • References: UNC HSRC, 2013; FHWA, 2018; Albee & Bobitz, 2021	
Road diets (roadway reconfiguration) • Usually converts a four-lane undivided roadway into a street with two through lanes, a center two-way left-turn lane, and sometimes two bicycle lanes. • Consider other treatments like pedestrian refuge islands, traffic calming, and speed management. • Often installed when traffic volumes are less than 25,000 vehicles/day. • References: UNC HSRC, 2013, 2014; Blackburn et al., 2018; FHWA, 2018; Thomas et al., 2018; Sanders et al., 2020; Albee & Bobitz, 2021	• Higher motor vehicle traffic-volumes (P/B) • Arterial and collector roadways (vs. local streets) (P) • More travel lanes / longer crossing distances (P) • Absence of more protected bicycle lanes (B)
Lane narrowing • Narrowing lanes to recommended minimums (9 ft rural, 10 ft regular or turn lanes, 11 ft for buses or trucks) can reduce vehicle speeds and discourage unsafe passing of people bicycling. • Often conducted with road diets, where additional space from narrowed lanes can be used for bicycle lanes or wider sidewalks. • References: UNC HSRC, 2013, 2014	• Higher speed limits (P/B)
Bicycle lanes • Various types of bicycle lanes provide greater separation in space: typical painted bike lanes, buffered bike lanes, or separated bike lanes (using parking, posts, vegetation, and/or curbs). • Refer to FHWA's *Bikeway Selection Guide* (Schultheiss et al., 2019) for specific preferred bikeway types for urban, urban core, suburban, rural town, and rural roadway contexts (based on vehicle speed and volume). • References: UNC HSRC, 2014; Sanders et al., 2020; Albee & Bobitz, 2021	• Absence of more protected bicycle lanes (B)

Countermeasure	*Risk factor(s)*
Rectangular rapid flashing beacons (RRFB) • Increase pedestrian conspicuity and driver yielding at uncontrolled marked crosswalks. • Especially effective at multilane crossings with speeds below 40 mph. • Consider installing on a median refuge rather than far side of roadway. • References: UNC HSRC, 2013, 2014; Blackburn et al., 2018; FHWA, 2018; Sanders et al., 2020; Albee & Bobitz, 2021	• Arterial and collector roadways (vs. local streets) (P) • More travel lanes / longer crossing distances (P)
Advance yield signs and markings • On multilane streets, use "YIELD Here to Pedestrians" signs and "shark's teeth" pavement markings 20-50 feet in advance of the marked crosswalk. • Additional treatments may be needed on higher-speed and -volume roads. • References: UNC HSRC, 2013; Blackburn et al., 2018; FHWA, 2018; Thomas et al., 2018; Sanders et al., 2020; Albee & Bobitz, 2021	• More travel lanes / longer crossing distances (P)
In-roadway yielding signs • On two/three-lane streets with speeds 30 mph or less, consider adding in-street "State Law YIELD to Pedestrians Within Crosswalk" signs. • Consider median islands to protect signs. • References: UNC HSRC, 2013; Blackburn et al., 2018; Thomas et al., 2018; Sanders et al., 2020	• Higher motor vehicle traffic volumes (P/B) • More travel lanes / longer crossing distances (P)
Longitudinal rumble strips and stripes on two-lane roads • On rural roads, consider milled edge line or shoulder rumble strips with bicycle gaps, especially on roads with shoulders wide enough for bicycling. • References: Albee & Bobitz, 2021	• Absence of rumble strips (B)
Intersections (non-signalized or signalized)	
Roundabouts • Can be implemented in urban and rural areas, and to replace two-way or all-way stop controlled intersections or signalized intersections. • Result in lower vehicular speeds and reduced conflicts. • Useful for transitioning between high- and low-speed environments. • Care should be taken to avoid adverse effects on bicycle safety (Poudel & Singleton, 2021). • References: UNC HSRC, 2013, 2014; FHWA, 2018; Sanders et al., 2020; Albee & Bobitz, 2021	• Arterial and collector roadways (vs. local streets) (P) • More turning vehicles / turn lanes (P/B) • Higher speed limits (P/B)
Curb radius reduction • Narrower curb radii reduce motor-vehicle turning speeds, thus improving driver awareness of and ability to stop for people walking and bicycling. • Consider prevalence of high turning volumes of large vehicles. • References: UNC HSRC, 2013, 2014; Sanders et al., 2020	• Higher speed limits (P/B) • More turning vehicles / turn lanes (P/B)
Raised crosswalk or speed table • Improves pedestrian conspicuity and forces drivers to travel more slowly through the intersection. • Consider when speeds at or below 30 mph and for traffic volumes below 9-25,000 vehicles/day. • References: UNC HSRC, 2013; Blackburn et al., 2018; FHWA, 2018; Sanders et al., 2020	• Higher speed limits (P/B)
Non-signalized intersections	
Mini traffic circles • Acting like miniature roundabouts in the middle of two-way stop-controlled intersections, mini traffic circles can reduce through-moving vehicle speeds and manage left turns.	• Higher speed limits (P/B)

Countermeasure	*Risk factor(s)*
• Consider on local roads, such as intersections with bicycle boulevards. • References: UNC HSRC, 2013, 2014; Sanders et al., 2020	
Signalized intersections	
Prohibit right turns on red (RTOR) • Prohibiting vehicles from turning right on red manages right-turn conflicts with pedestrians and may reduce driver encroachment into the crosswalk. • Consider right-turning vehicle volumes and pedestrian volumes. • References: UNC HSRC, 2013; FHWA, 2018; Sanders et al., 2020; Kittelson & Associates et al., 2022	• More turning vehicles / turn lanes (P/B)
Protected left-turn phase • Converting permissive left turns to protected phasing reduces conflicts between people walking/bicycling and left-turning vehicles. • Consider through and turning vehicle volumes, as well as signal timing and coordination. • References: UNC HSRC, 2013; Thomas et al., 2018; Sanders et al., 2020; Kittelson & Associates et al., 2022	• More turning vehicles / turn lanes (P/B)
Leading pedestrian interval (LPI) • Improve pedestrian visibility, reduce conflicts, and increase driver yielding at signalized intersections. • Consider especially at intersections with high turning volumes. • Commonly used to reduce conflicts with right-turning motor vehicles, but could also be implemented to reduce conflicts with left turns. • Recommended only when RTOR are prohibited and drivers follow the restriction; otherwise, additional conflicts may occur. • References: UNC HSRC, 2013; FHWA, 2018; Thomas et al., 2018; Sanders et al., 2020; Albee & Bobitz, 2021; Kittelson & Associates et al., 2022	• More turning vehicles / turn lanes (P/B)
Longer pedestrian phase • Helps pedestrians cross in time, especially for children, older adults, and people with disabilities. • Consider when pedestrian volumes are high or in areas with specific populations that have slower walking speeds. • Pedestrian push-buttons can include an extended button press that increases the crossing time. • Emerging technologies and passive detection (video, LiDAR, etc.) could automatically track slow-moving pedestrians/cyclists and extend the pedestrian/green phase only for those who need it. • References: UNC HSRC, 2013; FHWA, 2018; Thomas et al., 2018	• More travel lanes / longer crossing distances (P)
Exclusive pedestrian/bicycle phase • Prohibits turning vehicles while pedestrians are crossing in some or all directions (a.k.a. "pedestrian scramble" or "Barnes dance"). • Consider where pedestrian volumes are extremely high and turning vehicle volumes are also high, or when a diagonal bicycle crossing is needed. • References: UNC HSRC, 2013; FHWA, 2018; Kittelson & Associates et al., 2022	• More turning vehicles / turn lanes (P/B)
Bicycle treatments at intersections • Various types of bicycle facility treatments provide greater separation in space: protected intersections (with corner islands and bikeway setbacks), dedicated intersections (with corner wedges and hardened centerlines), bike boxes, two-stage turn queue boxes, intersection crossing markings, and thru lanes to the left of or shared with right-turn lanes.	• Higher motor vehicle traffic volumes (P/B) • Higher speed limits (P/B)

Countermeasure	*Risk factor(s)*
• Various types of bicycle signal timing/phasing provide greater separation in space: leading bicycle intervals (LBI), lagging left turns, exclusive bicycle phases ("bike scramble"), protected or protected-permissive bicycle phases, and bicycle signals. • Refer to NACTO's *Urban Bikeway Design Guide* (NACTO, 2014) and *Don't Give Up at the Intersection* guide (NACTO, 2019) for more details and contextual considerations. • References: UNC HSRC, 2014; Sanders et al., 2020; Kittelson & Associates et al., 2022	• More turning vehicles / turn lanes (P/B)

Notes about risk factors: P/B = pedestrian and bicycle, P = pedestrian only, B = bicycle only.

When selecting one or more of these countermeasures, careful consideration should be given to the appropriateness of the countermeasure for the specific locations and any potential non-safety consequences of implementing the treatment. For example, many treatments at signalized intersections (no RTOR, protected left-turn phasing, LPIs, longer or exclusive pedestrian phases) have the potential to reduce green times for major street thru movements and/or slightly reduce intersection capacity for motor vehicles. While many intersections operate below capacity for most if not all of the day, there may be specific locations or times of day when these treatments may cause large operational impacts that should be considered.

Beyond those listed in Table 5.2, other countermeasures may be suggested or implemented, especially those that are more applicable to local streets and countermeasures related to education, enforcement, or planning. To improve safety at school zones, the use of trained crossing guards, dedicated drop-off/pick-up locations, and walking/bicycling school buses can be implemented. Speed monitoring signs and trailers can provide feedback to drivers and increase awareness of and compliance with speeding issues at a local level. Targeted campaigns by law enforcement can increase awareness of traffic safety rules in specific locations, although they should focus on drivers instead of pedestrians and bicyclists, focus on education and warnings rather than citations, and be sensitive to concerns about over-policing in certain communities. Various educational initiatives can also be implemented, such as in-school bicycle/pedestrian safety education, driver training in preparation for licensure, and public awareness campaigns. See the PEDSAFE and BIKESAFE guides (UNC HSRC, 2013, 2014) for more information about these sorts of pedestrian and bicycle safety countermeasures.

Other sources provide more contextual guidance about when some of these countermeasures are appropriate and should be considered. For example:

- See the FHWA's *Guide for Improving Pedestrian Safety at Uncontrolled Crossing Locations* (Blackburn et al., 2018) for more details about the application of pedestrian crash countermeasures for uncontrolled crossing locations, based on motor vehicle volumes, speeds, and roadway configurations.
- See the FHWA's *Guide to Improve Pedestrian and Bicyclist Safety at Intersections* (Sanders et al., 2020) for recommendations and design tradeoffs regarding safety countermeasures at intersections.
- See the FHWA's *Bikeway Selection Guide* (Schultheiss et al., 2019) for recommendations about bikeway selection for segments in various contexts, based on motor-vehicle traffic speeds and volumes.
- See NACTO's *Urban Bikeway Design Guide* (NACTO, 2014) and *Don't Give Up at the Intersection* guide (NACTO, 2019) for design and operational strategies at intersections to improve safety and reduce conflicts for people bicycling and walking.
- See NCHRP Research Report 948 (Kittelson & Associates et al., 2020) for specific guidance about pedestrian and bicycle safety at alternative intersections and interchanges, such as diverging diamond interchanges (DDIs) and displaced left-turn (DLT) intersections.

5.4 Identification of Potential Treatment Sites and Countermeasures

Steps 4 and 5 in the systemic safety analysis process are to identify potential treatment sites and to select potential countermeasures. As described in the previous section, it is often useful to consider these two steps simultaneously or iteratively, as certain countermeasures are appropriate at specific types of sites. (See Table 5.2 and other resources for contextual details on countermeasure applicability.) Also, it is beyond the scope of this research project to identify which countermeasures are considered cost-effective and feasible (by UDOT staff and leadership) to implement on a systemic basis. Instead, this report presents a method by which UDOT staff can undertake such a process of selecting treatment sites, including when considering effective and feasible countermeasures for improving pedestrian and bicycle safety.

There are multiple ways to identify potential treatment sites. To recap, the goal of this step is to identify locations that have the greatest potential for reductions in future crashes as a result of applying systemic countermeasures that remove or mitigate risk factors that are present in those locations. There are two general methods that can be used to identify treatment locations, although it is often best to use them in conjunction.

One method focuses on the "greatest potential for crash reduction" criteria for location identification. This *ranking* method puts potential sites in decreasing order based on some measure of crash outcomes, namely crashes. It is not recommended to use observed crashes for ranking, since this is susceptible to regression-to-the-mean (RTM)—the phenomenon where sites with higher-than-average crashes will likely see fewer crashes in the future, more due to random chance than any treatments applied—and could have been done without the entire systemic analysis. Since crash reduction potential is future looking, a more reasonable choice would be predicted crashes derived from the application of the crash frequency models (SPFs) developed in Chapter 4.0. Another option is to apply the empirical Bayes (EB) approach, which combines the SPF-predicted crashes $N_{predicted}$ with observed crashes $N_{observed}$ based on weights w derived from the predictions and the overdispersion parameters ($k = 1/theta$) of the crash models, according to the following equations:

$$N_{expected(EB)} = w \times N_{predicted(SPF)} + (1 - w) \times N_{observed}$$

$$w = \frac{1}{1 + k \times \sum_{all\ study\ years} N_{predicted}}$$

The EB approach relies largely on the models but with some adjustment based on observed crash histories, in order to account for local risk factors that may not have been included in the SPFs. This ranking method has the benefit of focusing attention on locations with high (predicted and observed) crashes, where there could be great potential for reducing pedestrian and bicycle crashes in the future.

A second method focuses on the "applying countermeasures linked to risk factors" criteria for location identification. This *filtering* method considers an identified systemic countermeasure and then filters locations based on the presence of one or more risk factors associated with that countermeasure and/or locations with conditions where that treatment is recommended or appropriate. This method also has the benefit of allowing the consideration of agency guidelines for where and when to apply a particular countermeasure; for example, road diets may only be considered for multilane streets within a certain range of AADT.

It also may be ideal to consider both ranking and filtering methods in conjunction. For example, one might consider a particular countermeasure and initially filter locations with associated risk factors and appropriate conditions for the treatment. Sometimes many more locations are identified than can be treated with available funding. If so, treatment locations can then be initially prioritized based on the rankings of predicted or expected crashes.

5.4.1 Interactive Application to Identify Treatment Locations

In order to aid in the identification of potential treatment sites using both ranking and filtering methods, this research project developed an interactive interface including map and table views. There are separate screens for each location type: segments or mid-block locations, non-signalized intersections, and signalized intersections. The interface has been built in R Shiny, which can be deployed to the web; the features and functionality could be implemented (and improved) in a different software or platform. Figure 5.1 shows a screenshot of the interface, showing the "segments or mid-block locations" tab for example.

First, the analyst selects a crash outcome of interest, which is the metric by which locations will be ranked. There are currently eight options, encompassing the pedestrian A models and bicycle B models estimated in Chapter 4.0 (all vs. fatal and serious injury), as well as options for using the model-predicted crashes directly or using the EB method (combined with information on observed crashes). The A models are recommended for pedestrian crashes because they contain the most explanatory variables. The B models are recommended for bicycle crashes because the Strava data in the A models might bias the results to recreational locations. For segments, an additional option lets the analyst calculate crash rates (crashes per 0.10-mile) instead of total crashes, to account for varying segment lengths.

Second, the analyst may select one or more filters for screening the locations. They must select a variable, a condition, and one or more values. Currently, all variables are available to be used for filtering, including location, roadway and community characteristics, exposure, and even observed or predicted crashes. Conditions include the typical greater than or less than (as well as “or equal to” versions; not available for categorical variables), equal or not equal to, and a multiple selection option. For continuous numeric variables, values can be any number; for categorical variables or the multiple selection option, values are selected from a list. After applying one filter, another one can be determined. Clicking the button refreshes the map and table to conform to the new crash outcome or filter(s).

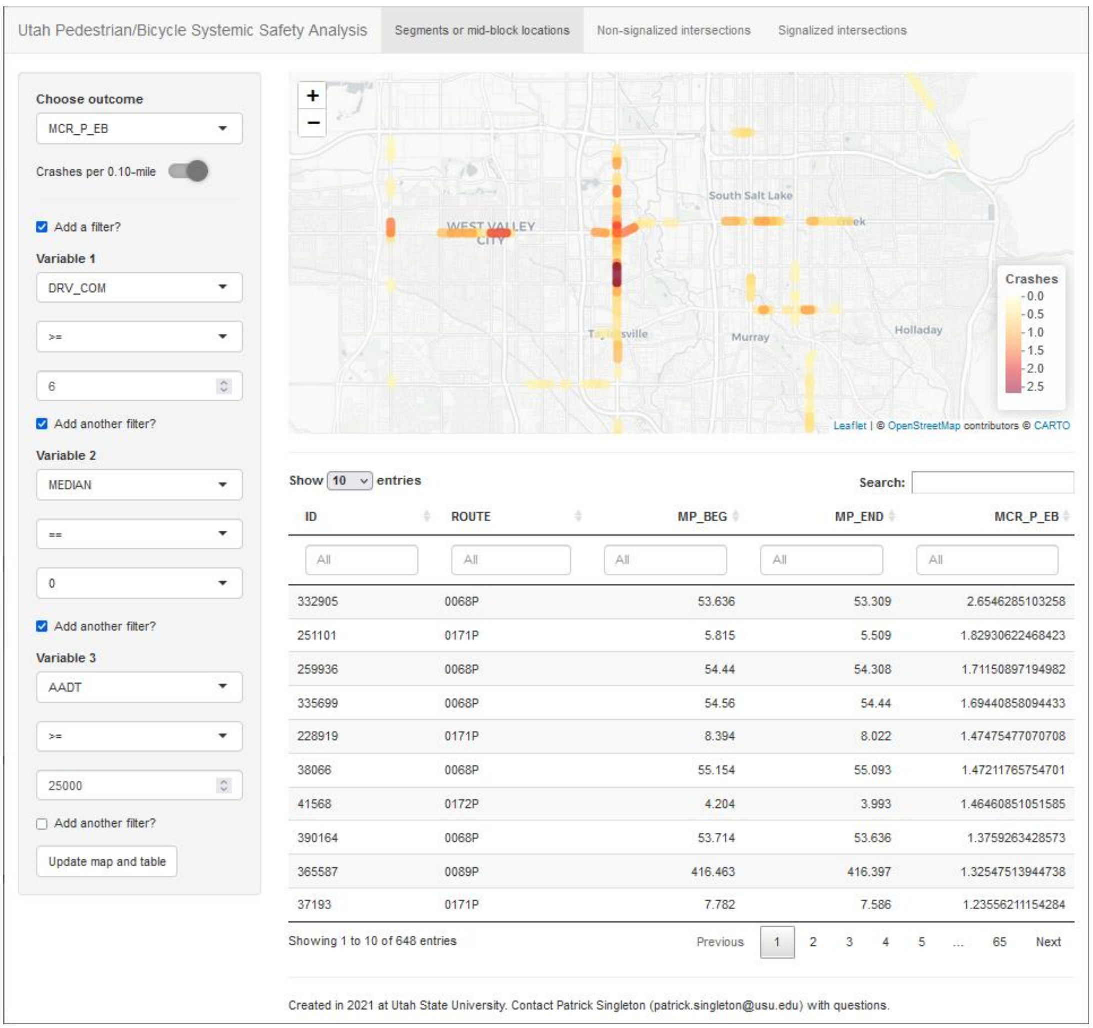

Figure 5.1 Example of Interactive Interface for Segments or Mid-Block Locations

For example, consider the roadway crash countermeasure "corridor access management," which is designed to reduce conflicts between turning motor vehicles and people walking and bicycling by closing, consolidating, or relocating driveways. Medians are a related possible treatment, and may be most effective on busier streets. Figure 5.1 shows how the interactive interface could be used to identify potential treatment locations for this countermeasure. First, three filters are applied: segments with many commercial driveways (6+), without a median (type = no island), and with high traffic volumes (AADT $\geq$ 25,000). These filters limit the potential locations to 145, of which several high-ranking sites (based on model-predicted pedestrian crash frequency) are in West Valley City, Taylorsville, and South Salt Lake, especially along Redwood Road (SR-68) and 3300/3500 S (SR-171). A systemic application of this countermeasure would be to consider driveway consolidation and the installation of medians in selective locations along these corridors.

5.4.2 Potential Treatment Locations for Pedestrian and Bicycle Crashes

Regardless of specific countermeasures, it is useful to consider locations that rank highly on the different crash outcomes. The following tables show the top-ten locations of each type in terms of predicted or expected pedestrian and bicycle crashes (total, and fatal and serious injury). The lists are based on the most fully specified models—Models A for pedestrian crashes, the ones with the most variables; Models B for bicycle crashes, given that Strava data in A might skew the findings towards recreational areas—so there may be other sites that should also be considered (see the interface for rankings). The lists also utilize the EB method to incorporate some influence of observed crashes.

Table 5.3 shows potential treatment sites for pedestrian and bicycle crashes at segments or mid-block locations, ranked by total crashes. Table 5.4 is ranked by crash rate (crashes per tenth-mile), to account for varying segment lengths. Most high-ranking sites are located on multilane arterials in Salt Lake County, with several located on 3300/3500 S (SR-171), Redwood Road (SR-68), State Street (US-89), and 400 N (SR-186). For example, Redwood Road (SR-68) just north of 4100 N in West Valley City ranked first or second on all metrics, and is a multilane highway near apartments, grocery and convenience stores, and major bus stops. A few other high-ranking sites are located on multilane arterials that are also in commercial areas of Provo, Orem, Roy, Ogden, and Logan.

Table 5.5 shows the highest-ranking potential treatment sites for pedestrian and bicycle crashes at non-signalized intersections. These sites were not nearly as concentrated as for other location types, occurring all along the Wasatch Front (from North Ogden to Payson), as well as in Tooele and Washington. Several identified sites were at driveways or freeway ramps, while others were located at places with known traffic signals. This finding illustrates the difficulties in developing safety performance functions for non-signalized intersections, due to the difficulty of identifying intersections; see Section 7.1.2 for more details about how to mitigate this limitation.

Table 5.6 shows the highest-ranking potential treatment sites for pedestrian and bicycle crashes at signalized intersections. Most of them are located on multilane arterials in Salt Lake County, with several located on 3300/3500 S (SR-171), State Street (US-89), and Redwood Road (SR-68). Many of these locations overlap with the high-ranking segment locations.

Table 5.3 Potential Treatment Sites for Segments or Mid-Block Locations (Total Crashes)

	All crashes		*Fatal and serious injury crashes*	
Location	*Rank*	*Crashes / 10-yr*	*Rank*	*Crashes / 10-yr*
Pedestrian crashes				
Redwood Rd (SR-68), 3900 S to 4100 S, West Valley City	1	8.70	1	2.47
3500 S (SR-171), 4000 W to Bangerter Hwy, West Valley City	2	5.62	2	1.99
3500 S (SR-171), Redwood Rd to 1400 W, West Valley City	3	5.48	3	1.42
7200 S (SR-48), 180 W to State St, Midvale	4	4.22	6	0.95
5600 W (SR-172), Hunter Dr to 3500 S, West Valley City	5	3.09		
Bangerter Hwy (SR-154), 3500 S to 4100 S, West Valley City	6	2.84		
Bangerter Hwy (SR-154), 4700 S to 5400 S, Taylorsville	7	2.65	5	1.03
3500 S (SR-171), Decker Lake Dr to 1940 W, West Valley City	8	2.42		
Redwood Rd (SR-68), 4800 S to 5000 S, Taylorsville	9	2.39	4	1.10
Redwood Rd (SR-68), 3395 S to 3500 S, West Valley City	10	2.27		
State St (SR-89), E Ford Ave to Winslow Ave, South Salt Lake			7	0.93
Redwood Rd (SR-68), 4100 S to 4200 S, Taylorsville			8	0.85
Redwood Rd (SR-68), 3100 S to 3300 S, West Valley City			9	0.81
3300 S (SR-171), 300 E to 400 E, South Salt Lake			10	0.79
Bicycle crashes				
State St (US-89), 1720 N to Riverside Ave, Provo	1	3.32		
1900 W (SR-126), 5700 S to 5950 S, Roy	2	3.21		
3500 S (SR-171), 4000 W to Bangerter Hwy, West Valley City	3	3.13		
Redwood Rd (SR-68), 4800 S to 5000 S, Taylorsville	4	3.12		
State St (US-89), 5770 S to 5900 S, Murray	5	3.11		
400 S (SR-186), 700 E to 800 E, Salt Lake City	6	3.09		
University Ave (US-189), 1450 N to 1230 N / Cougar Blvd, Provo	7	2.89		
Main St (US-91), 300 N to 200 N, Logan	8	2.86		
400 S (SR-186), 600 E to 700 E, Salt Lake City	9	2.82		
Redwood Rd (SR-68), 3900 S to 4100 S, West Valley City	10	2.64		
Mountain View Crd NB (SR-85), 4700 S to 5400 S, West Valley City			1	0.39
3300 S (SR-171), 2700 E to 2900 E, Millcreek			2	0.29
State St (SR-186), Hillside Ave to 200 N, Salt Lake City			3	0.27
State St (US-89), Columbia Ln to Cove Point Ln, Orem			4	0.26
400 S (SR-186), 900 E to Fletcher Ct, Salt Lake City			5	0.26
7800 S (SR-48), Elk Ridge Dr to 3200 W, West Jordan			6	0.25
Hill Field R (SR-232), Hwy 193 to 2675 N, Layton			7	0.25
3500 S (SR-171), Redwood Rd to 1400 W, West Valley City			8	0.24
Alpine Scenic (SR-92), FR 114 to Mt. Timpanogos Trhd, Utah County			9	0.23
Alpine Scenic (SR-92), Eleanor's Rd to Big Pine Cyn Rd, Utah County			10	0.23

Table 5.4 Potential Treatment Sites for Segments or Mid-Block Locations (Crashes per Tenth-Mile)

	All crashes		*Fatal and serious injury crashes*	
Location	*Rank*	*Crashes / 0.1-mi / 10-yr*	*Rank*	*Crashes / 0.1-mi / 10-yr*
Pedestrian crashes				
Redwood Rd (SR-68), 3900 S to 4100 S, West Valley City	1	2.65	2	0.75
State St (SR-186), 200 S to Broadway, Salt Lake City	2	2.63		
State St (US-89), Baird Ave to Helm Ave, South Salt Lake	3	2.07	1	1.06
3500 S (SR-171), 4000 W to Bangerter Hwy, West Valley City	4	1.83	3	0.65
Redwood Rd (SR-68), 3395 S to 3500 S, West Valley City	5	1.71		
Redwood Rd (SR-68), 3300 S to 3395 S, West Valley City	6	1.69	10	0.51
State St (US-89), Upton Pl to 900 S, Salt Lake City	7	1.67		
3500 S (SR-171), Redwood Rd to 1400 W, West Valley City	8	1.47		
Redwood Rd (SR-68), Shelly Ave to Sunset Ave, West Valley City	9	1.47		
5600 W (SR-172), Hunter Dr to 3500 S, West Valley City	10	1.46		
Washington Blvd (US-89), 2nd St to 3rd St, Ogden			4	0.57
Redwood Rd (SR-68), Shelly Ave to Sunset Ave, West Valley City			5	0.57
State St (US-89), Ford Ave to Winslow Ave, South Salt Lake			6	0.56
3300 S (SR-171), 300 E to 400 E, South Salt Lake			7	0.52
3500 S (SR-171), 3200 W to 3050 W, West Valley City			8	0.51
Redwood Rd (SR-68), 4100 S to 4200 S, Taylorsville			9	0.51
Bicycle crashes				
Main St (US-91), 300 N to 200 N, Logan	1	2.16		
State St (SR-186), S Temple to 100 S, Salt Lake City	2	2.11		
400 S (SR-186), 700 E to 800 E, Salt Lake City	3	2.06		
Redwood Rd (SR-68), 4200 S to 4270 S, Taylorsville	4	1.93		
400 S (SR-186), 600 E to 700 E, Salt Lake City	5	1.88		
State St (US-89), 1120 W to 1850 N / 950 W, Provo	6	1.88		
3500 S (SR-171), 3050 W to 3030 W, West Valley City	7	1.81		
State St (US-89), 400 N to 300 N, Orem	8	1.59		
400 S (SR-186), 500 E to 600 E, Salt Lake City	9	1.56		
State St (US-89), Claybourne Ave to Ideal Ln, South Salt Lake	10	1.51		
State St (SR-186), Hillside Ave to 200 N, Salt Lake City			1	0.37
400 S (SR-186), 900 E to Fletcher Ct, Salt Lake City			2	0.28
500 S (SR-186), Isabella Ct to 1100 E, Salt Lake City			3	0.22
3300 S (SR-171), 2600 E to Oakwood Ave, Millcreek			4	0.15
4430 S (SR-266), Wallace Ln to 2950 E, Holladay			5	0.15
3300 S (SR-171), Oakwood Ave to 2700 E, Millcreek			6	0.14
700 E (SR-71), 700 S to 800 S, Salt Lake City			7	0.14
3300 S (SR-171), 1575 E to Imperial St, Millcreek			8	0.14
300 N (SR-186), Wall St to State St, Salt Lake City			9	0.14
4430 S (SR-266), Aspen Hollow Ln to Leo Wy, Holladay			10	0.14

Table 5.5 Potential Treatment Sites for Non-Signalized Intersections

	All crashes		*Fatal and serious injury crashes*	
Location	*Rank*	*Crashes / 10-yr*	*Rank*	*Crashes / 10-yr*
Pedestrian crashes				
300 N (SR-186) & State St (SR-186), Salt Lake City	1	1.45		
Church St & Main St (SR-126), Layton	2	1.16	7	0.05
30th St (SR-79) & Jefferson Ave, Ogden	3	0.88	2	0.09
24th St (SR-53) & Wall Ave (SR-204), Ogden	4	0.71		
3100 S & Hwy 89 (US-89), North Salt Lake	5	0.71	8	0.05
driveway to SLCC & Redwood Rd (SR-68), Taylorsville	6	0.67		
S Campus Dr (SR-282) & driveway to Stadium, Salt Lake City	7	0.57		
200 S & 500 E (SR-180), American Fork	8	0.56		
400 N (SR-147) & 300 W, Spanish Fork	9	0.46		
50 S / 1100 N & N Country Blvd (SR-129), American Fork	10	0.34	3	0.08
7800 S (SR-48) & ramps at Bangerter Hwy (SR-154), West Jordan			1	0.25
S Campus Dr (SR-282) & 1580 E (SR-282), Salt Lake City			4	0.06
600 S & University Ave (US-189), Provo			5	0.06
30th St (SR-79) & Adams Avenue, Ogden			6	0.05
3300 S (SR-171) & ramps at I-15 (I-15), South Salt Lake			9	0.05
9000 S (SR-209 & State St (US-89), Sandy			10	0.04
Bicycle crashes				
24th St (SR-53) & Wall Ave (SR-204), Ogden	1	2.65		
200 N & 500 W (US-89), Provo	2	0.91		
50 S / 1100 N & N Country Blvd (SR-129), American Fork	3	0.59	4	0.16
Layton Pkwy (SR-126) & west ramps at I-15 (I-15), Layton	4	0.46		
State St (SR-9) & Coral Canyon Blvd, Washington	5	0.44	3	0.17
1100 N & Washington Blvd (SR-235), Harrisville / Ogden	6	0.44		
4500 S (SR-266) & west ramps at I-15 (I-15), Murray	7	0.42	1	0.23
400 N & Main St (SR-198), Payson	8	0.42		
500 N & Main St (SR-36), Tooele	9	0.42		
300 N (SR-186) & State St (SR-186), Salt Lake City	10	0.41		
7800 S (SR-48) & ramps at Bangerter Hwy (SR-154), West Jordan			2	0.21
north ramps at I-84 (I-84) & Hwy 89 (US-89), Uintah			5	0.12
12300 S & west ramps at I-15 (I-15), Draper			6	0.11
Riverdale Rd (SR-26) & ramps at I-84 (I-84), Riverdale			7	0.10
9400 S & State St (US-89), Sandy			8	0.10
12300 S & east ramps at I-15 (I-15), Draper			9	0.10
N Temple & Redwood Rd (SR-68), Salt Lake City			10	0.07

Table 5.6 Potential Treatment Sites for Signalized Intersections

	All crashes		*Fatal and serious injury crashes*	
Location	*Rank*	*Crashes / 10-yr*	*Rank*	*Crashes / 10-yr*
Pedestrian crashes				
7104 - 4100 S & Redwood Rd (SR-68), West Valley City/Taylorsville	1	20.60	6	1.77
7155 - 3300 S (SR-171) & State St (US-89), South Salt Lake	2	13.24	5	1.79
7283 - 3500 S (SR-171) & 3600 W, West Valley City	3	12.67		
7157 - 4500 S (SR-266) & State St (US-89), Murray	4	12.49	10	1.52
7102 - 3500 S (SR-171) & Redwood Rd (SR-68), West Valley City	5	12.20	7	1.73
7168 - 7200 S (SR-48) & State St (US-89), Midvale	6	11.51		
5118 - 700 S (SR-193) & State St (SR-126), Clearfield	7	11.37		
7194 - 7800 S & 700 E (SR-71), Sandy	8	10.85		
7282 - 3500 S (SR-171) & 4000 W, West Valley City	9	10.76		
7207 - Fort Union Blvd & 900 E (SR-71), Midvale	10	10.67	1	2.65
7110 - 5400 S (SR-173) & Redwood Rd (SR-68), Taylorsville			2	2.37
7115 - 7000 S (SR-48) & Redwood Rd (SR-68), West Jordan			3	2.22
5019 - 28th St & Washington (US-89), Ogden			4	2.00
7291 - 3300 S (SR-171) & 900 W, South Salt Lake			8	1.63
7216 - 500 S (SR-186) & Guardsman Wy/1580 E (SR-282), Salt Lake City			9	1.59
Bicycle crashes				
7155 - 3300 S (SR-171) & State St (US-89), South Salt Lake	1	9.11		
7104 - 4100 S & Redwood Rd (SR-68), West Valley City/Taylorsville	2	8.64		
7295 - 3300 S (SR-171) & West Temple, South Salt Lake	3	8.19		
7102 - 3500 S (SR-171) & Redwood Rd (SR-68), West Valley City	4	7.57		
6417 - University Pkwy (SR-265) & University Ave (US-189), Provo	5	6.54	10	0.53
7148 - 1300 S & State St (US-89), Salt Lake City	6	6.50		
6448 - 1720 N & State St (US-89), Provo	7	6.40		
6415 - 1230 N (Bulldog) & University Ave (US-189), Provo	8	6.36		
7331 - 5400 S (SR-173) & 2700 W, Taylorsville	9	6.15		
7242 - 400 S (US-89) & 200 W, Salt Lake City	10	5.54		
7140 - 200 S & State St (SR-186), Salt Lake City			1	1.16
7184 - 900 S & 700 E (SR-71), Salt Lake City			2	1.10
7095 - 1700 S & Redwood Rd (SR-68), Salt Lake City			3	0.88
7174 - 9000 S (SR-209) & State St (US-89), Sandy			4	0.85
5123 - 650 N (SR-103) & Main St (SR-126), Clearfield			5	0.72
7192 - 3900 S & 700 E (SR-71), South Salt Lake/Salt Lake County			6	0.58
7187 - 2100 S & 700 E (SR-71), Salt Lake City			7	0.55
7147 - 900 S & State St (US-89), Salt Lake City			8	0.55
4010 - 3900 S & Highland Dr (1650 E), Salt Lake County/Holladay			9	0.54

5.5 Summary

This chapter applied three steps in the systemic safety analysis process for pedestrian and bicycle safety: determination of risk factors, identification of potential treatment sites, and selection of potential countermeasures. First, risk factors for pedestrian and bicycle crashes were determined from the literature review and the crash frequency model results of the previous chapter. Second, a list of countermeasures related to those risk factors was developed. Third, different filtering and screening methods for identifying treatment locations were described, and an interactive interface was presented to aid in treatment site selection.

6.0 CONCLUSIONS

6.1 Summary

The objective of this systemic analysis of bicycle and pedestrian safety in Utah was to identify risk factors, potential treatment sites, and potential countermeasures. To accomplish this objective, this project undertook several major tasks, described in the preceding chapters:

1. Chapter 2.0 presented a **literature review**, including best practices for systemic safety analysis, methods for risk factor identification, and risk factors for pedestrian and bicycle crashes as found in previous research.
2. Chapter 3.0 described the process of **data collection** and assembly, including identifying study locations (segments or mid-block locations, signalized intersections, and non-signalized intersections), assigning crashes (pedestrian- or bicycle-involved, from 2010 through 2019), and assembling data on exposure, roadway characteristics, and community characteristics (from various sources).
3. Chapter 4.0 documented the **data analysis** process, including the results of 48 Poisson or negative binomial regression models, segmented by: mode (pedestrian or bicycle), location type (segments, non-signalized or signalized intersections), crash type (all or fatal and serious injury), network type (state-only or state and federal-aid roads), and variable specification (with or without exposure).
4. Chapter 5.0 presented **applications** of the study's results, including the determination of risk factors (from the literature and the models), the development of a list of potential countermeasures (linked to specific risk factors), the use of an interactive web app to identify potential treatment sites (through filtering and/or ranking), and lists of the top-ten potential treatment sites (by mode and location type) based on anticipated pedestrian/bicycle crashes.

The remainder of this chapter summarizes the key findings from this effort and documents limitations and challenges that could be overcome in future systemic analyses of bicycle and pedestrian safety.

6.2 Findings

6.2.1 Systemic Approach Offers Improved Understanding of Bicycle/Pedestrian Safety

The systemic approach to safety analysis conducted in this project provided an improved understanding of the issues surrounding bicycle and pedestrian safety in Utah. First, it offered a proactive means of dealing with the limitations introduced by the highly dispersed nature of pedestrian and bicycle crashes (many sites with only a few crashes). Instead of relying on a more traditional site-based hot-spot safety analysis, the systemic approach utilized empirical relationships between crash frequencies and roadway/transportation/contextual factors to determine risk factors, later using those risk factors to determine locations with treatment potential. Additionally, the systemic approach identified pedestrian/bicycle risk factors using the best of both worlds: deep insights from previous literature and research in other places over many years, as well as local context and Utah-specific findings taken from newly estimated crash frequency models. Finally, the application of empirical-Bayes approaches to crash frequency estimation (and ranking of potential treatment sites) considers both model-identified risk factors as well as crash histories that account for other factors not included in the models. The findings from this research should be considered alongside prior and ongoing research (e.g., Burbidge, 2016) into pedestrian and bicycle safety in Utah.

6.2.2 Literature and Data Analysis Identified Various Bicycle Crash Risk Factors

A review of the literature and the crash frequency models identified several risk factors for bicycle crashes in the areas of measures of exposure, transportation (roadway geometry and traffic) characteristics, and neighborhood community (land use, built environment, and sociodemographic) characteristics. The following factors (summarized in Table 5.1) were associated with more bicycle crashes (a positive association) in the literature and/or models:

- *Measures of exposure*: more motor vehicle traffic (including turning vehicles), greater bicycle volumes (but the “safety in numbers” effect implies lower bicycle crash rates).
- *Transportation (roadway geometry and traffic) characteristics*: more intersection approaches/legs, longer crossing distances, narrower lanes (without bicycle facilities), more turn lanes, absence of a right shoulder/curb lane or rumble strips, absence of a

median/island or right barrier, absence of a channelized right-turn lane, absence of more robust bicycle infrastructure (from shared lane markings: “sharrows”) and regular lanes to protected lanes and off-street paths), more driveways (especially to commercial and residential properties), steeper roadway grades, more bus/transit stops/stations (stronger association with far-side than with near-side bus stops).

    - Characteristics like arterial/collector roadways (or state highways), two-way streets (vs. one-way), and higher speed limits were associated with more severe crashes, rather than more frequent crashes.

- *Neighborhood community (land use, built environment, and sociodemographic) characteristics*: denser areas (especially employment; population density likely a proxy for more bicycling), areas with larger low-income populations, more zero-vehicle households, more people with a disability, areas with larger minority (Hispanic or non-white) populations.

6.2.3 Literature and Data Analysis Identified Various Pedestrian Crash Risk Factors

The literature review and models of crash frequencies also identified several risk factors for pedestrian crashes in the areas of exposure, transportation, and neighborhood community characteristics. The following factors (summarized in Table 5.1) were associated with more pedestrian crashes (a positive association) in the literature and/or models:

- *Measures of exposure*: more motor vehicle traffic, greater pedestrian volumes (but the “safety in numbers” effect implies lower pedestrian crash rates).
- *Transportation (roadway geometry and traffic) characteristics*: arterial/collector roadways (or state highways), two-way streets (vs. one-way), more intersection legs/approaches, more travel lanes, longer crossing distances, more turn lanes, presence of two-way left-turn lanes, absence of a median/island or right barrier, presence of on-street parking, more driveways (especially to commercial and residential properties), steeper roadway grades, more bus/transit stops/stations (stronger association with far-side than with near-side bus stops).
    - Characteristics like greater percentage of trucks and higher speed limits were associated with more severe crashes, rather than more frequent crashes.

- *Neighborhood community (land use, built environment, and sociodemographic) characteristics*: denser and more mixed-use areas (for population density only when not accounting for pedestrian exposure), areas with larger low-income populations, more zero-vehicle households, more people with a disability, areas with larger minority (Hispanic or non-white) populations.

6.2.4 Potential Systemic Countermeasures for Bicycle/Pedestrian Safety Were Noted

Based on a variety of published sources about bicycle and pedestrian safety (including FHWA publications and NCHRP research reports), many potential countermeasures were suggested. The countermeasures could be applied in a systemic way (at multiple high-risk locations) in order to treat specific risk factors identified through the literature and the models. Potential countermeasures (detailed in Table 5.2) are summarized by the location(s) to which they apply:

- *All locations (segments and intersections)*: corridor access management, medians and pedestrian refuge islands, appropriate speed limits for all road users, high-visibility crosswalk markings, curb extensions with parking restrictions, lighting, pedestrian hybrid beacons (PHB), grade-separated crossings.
- *Segments or mid-block locations*: walkways, road diets (roadway reconfiguration), bicycle lanes, rectangular rapid flashing beacons (RRFB), advance yield signs and markings, in-roadway yielding signs, longitudinal rumble strips and stripes on two-lane roads.
- *Intersections (non-signalized and/or signalized)*: roundabouts, raised crosswalk or speed table, mini traffic circles, prohibit right turns on red (RTOR), protected left-turn phase, leading pedestrian interval (LPI), longer pedestrian phase, exclusive pedestrian phase, bicycle treatments at intersections.

6.2.5 Interactive Interface Can Help Identify Treatment Locations via Filtering/Ranking

The project also offered guidance (see Section 5.4) on methods for identifying potential treatment locations where applying the systemic countermeasures could help to improve bicycle and pedestrian safety. Generally, a combination of filtering and ranking could be used: for example, selecting a potential countermeasure, filtering locations with associated risk factor, and ranking locations based on an empirical-Bayes estimate of crashes. This project also developed a sample interactive interface that could be adapted to aid in this filtering/ranking process. The interface includes map and table views for each location type (segments/mid-block locations, non-signalized, and signalized intersections). Locations can be filtered according to multiple variables and their attributes (location, exposure, transportation, and community characteristics), and then remaining locations are ranked according to some metric (e.g., expected crash frequency). For such a system or interface to be used most effectively, it is recommended to be integrated into UDOT's existing set of roadway safety management tools and procedures (e.g., Numetric safety analysis).

6.3 Limitations and Challenges

This research was not without challenges that resulted in limitations with respect to the study's data, analysis, results, and findings. The following paragraphs describe some of these study limitations, as well as opportunities to overcome the challenges.

Data limitations prevented the testing of some potential risk factors for pedestrian/bicycle crashes. Although this study assembled large quantities of data for many locations, it was unable to include some variables in the models that past literature has identified as potential risk factors for pedestrian and/or bicycle crashes; see "n/a" entries in Table 5.1. Most notably, this included the presence of on-street parking and/or density of driveways, in addition to other variables for some location types. Additionally, several characteristics that would likely improve the prediction of bicycle and pedestrian crashes were unable to be included, such as turning motor vehicle volumes at intersections, sidewalk and crosswalk presence (and type, size, quality, etc.), and the condition of street lighting anywhere. Data on these topics were either unavailable or in a format that was difficult to assemble for modeling purposes. If these data were available in an easy-to-use format, the models may have been able to identify additional risk factors, thus adding potential countermeasures to the toolbox.

The measure of bicycle exposure used in this study, while somewhat useful, still had significant limitations. Although the Strava Metro data provided a measure of exposure for all locations, it represents a small and non-representative sample of all bicycle trips that is biased towards recreational uses and recreational locations. This may have been the reason for the non-significance of Strava bicycle volumes in the non-signalized intersection models (see Table 4.55) and the cause of some less intuitive spatial predictions (of bicycle crash frequencies) of models with exposure (A and C). Because the share of bicycle trips recorded by Strava varies between regions and even neighborhoods, it may be difficult to create adjustment factors to adequately adjust for this non-representativeness. Therefore, other data sources of bicycle volume or exposure data may need to be explored, such as those relying on location-based services data.

Many of the roadway and traffic characteristics were defined only for state highway segments, not for federal-aid and local segments, and exposure data was not available everywhere (especially for pedestrian exposure). Together, these limitations greatly restricted the available sample sizes, thus limiting the findings in multiple ways. First, many bicycle and pedestrian crashes occurred away from the state (and federal-aid) network, meaning they could not be used in this study to identify risk factors or treatment locations. Second, the lack of many roadway and traffic characteristics data for non-state routes meant that separate models had to be estimated, trading-off larger sample sizes (but fewer independent variables, models C and D) vs. more independent variables (but fewer locations, models A and B). It could be that relationships between crashes and some of these potential risk factors differ for state highways vs. local roads, but this possibility could not be examined. Third, a similar tradeoff had to be made regarding the inclusion (smaller sample sizes, models A and C) vs. exclusion (larger sample sizes, models B and D) of pedestrian and bicycle exposure. If such data on roadway and traffic characteristics and exposure were available in more locations (including for non-state facilities), the models might have been able to identify more risk factors or explained more of the variation in crash frequencies across locations.

Relatedly, most roadway and traffic characteristics were defined only for segments, not for intersections. This greatly complicated data assembly for signalized and especially for non-signalized intersections, for several reasons. First, intersections were hard to define because there was not a statewide database of (non-signalized) intersection locations or characteristics. Analysts had to derive junctions from nodes in a street network geodatabase and use heuristics to determine which were truly non-signalized intersections, rather than signalized intersections, driveway entrances, channelized turns, etc. Second, intersection roadway and traffic characteristics did not exist and had to be constructed from characteristics of the adjacent/approaching roadways. Again, this required some analyst decisions about which segments were adjacent and how to calculate a single intersection value from multiple segment attributes. Third, even some roadway segment characteristics were difficult to define, due to varying definitions of segment start/end points and multiple matches when conducting spatial buffering. Altogether, these procedures likely resulted in some errors in (non-signalized intersection) definition or characteristics, especially in complex areas such as around freeway interchanges. A statewide database containing verified intersection locations and attributes would greatly improve the data collection and modeling process.

A temporal mismatch between crashes and other (roadway, traffic, exposure, community) characteristics data also potentially limited the robustness of the model results. Crashes occurred anywhere from 2010 through 2019, a ten-year time span. The other characteristics used in the models were collected for a varying single point in time: 2017-18 for pedestrian exposure, 2019 for bicycle exposure, 2017 for motor vehicle traffic volumes, late 2019 (or earlier) for roadway characteristics. Due to small numbers of crashes and lack of temporally varying independent variables, all of these data were combined into a single observation at each location. In other words, the crashes being modeled could have occurred anytime over a ten-year period, while the roadway/traffic characteristics being modeled were for a single time period. While this difference may not matter for characteristics (e.g., land use, number of lanes) or in locations (e.g., built-up areas) that change fairly slowly, a greater discrepancy could be expected for other characteristics (e.g., traffic volumes) and in rapidly growing or redeveloping areas, especially on the urban periphery. The consequence of this temporal mismatch is unknown, but potentially includes some bias in the modeled relationships and identified risk factors. Solving this temporal mismatch problem would require the retention of historical roadway characteristics data.

The pedestrian and bicycle crash data also contained inherent limitations that could not be overcome in this study. Reported crash data omits collisions that are not required to be reported to the police, including single-bicycle crashes or collisions between people walking and bicycling but not a motor vehicle. More notably, reported crash data is known to underreport certain kinds of reportable crashes, especially crashes with less severe injuries and pedestrian/bicycle crashes (Doggett et al., 2018). Thus, the model predictions of crash frequencies may be smaller than in reality, thus slightly underestimating what is a bigger problem regarding pedestrian/bicycle safety. One solution that is being attempted (e.g., Hosseinzadeh et al., 2022) is the merging of crash data with hospital records, although significant challenges remain to be overcome. Another strategy is to measure more common events often called surrogate safety measures: conflicts or near misses, which are assumed to correlate with crashes (e.g., Tarko, 2021).

The data analysis methods could also be enhanced to include emerging practices. While the Poisson and negative binomial regression models employed in this study are state-of-the-practice methods, state-of-the-art techniques emerging from the research literature—especially machine-learning methods—could enhance the modeling effort and improve risk factor identification and countermeasure/treatment recommendations. For example, gradient-boosted decision trees have been used in a few studies to predict crashes (e.g., An et al., 2022). Decision trees use a data-driven approach to classify outcomes (e.g., crash frequencies) by splitting or partitioning the data based on best-fit breakpoints in multiple independent variables (e.g., potential risk factors). Gradient-boosted decision trees do this process multiple times and average the results. One output of this method is the “importance” of a particular variable, which identifies how useful it was in defining the splits/breakpoints to classify the outcomes. Variables with high importance could be considered candidate risk factors. A second output of this method is a partial dependency plot for each independent variable, showing how the marginal effect of that variable on the outcome changes across the range of observed values. These plots can show non-linear relationships that may be useful to model. To summarize, creating machine-learning methods (such as gradient-boosted decision trees) could be a useful first step—generating lists of risk factors and non-linearities—prior to estimating more conventional (Poisson or negative binomial) crash frequency models.

7.0 RECOMMENDATIONS AND IMPLEMENTATION

7.1 Recommendations

Based on the limitations noted in the previous chapter (Section 6.3), the following paragraphs describe several recommendations, especially for actions in the area of data, that would improve future systemic analyses of bicycle and pedestrian safety in Utah.

7.1.1 Continue Improving Data Collection for Walking and Bicycling

Utah has made great strides in recent years to improve all sorts of active transportation data, including existing and planned facilities, current volumes and estimated demand, and comfort/stress. Recent work by staff at UDOT (Traffic & Safety, Planning), metropolitan planning organizations (MPO) (like the Wasatch Front Regional Council (WFRC)), and others have enabled existing bicycle facilities to be added to the common road centerline file used as the basis for statewide roads and routes databases (https://gis.utah.gov/bike-related-gis-data-resources/). UDOT-funded research has helped develop the use of pedestrian push-button data at traffic signals to estimate pedestrian volumes throughout the network (Singleton, Runa, & Humagain, 2020; Singleton, Park, & Lee, 2021). Information about potential bicycle and pedestrian demand as well as planned active transportation projects are now available on UDOT (http://udot.utah.gov/atmap) and WFRC (http://arcg.is/0afeDS) websites. This work should continue, especially in the following ways.

While information on existing bicycle facilities is greatly beneficial, additional information on **pedestrian-related facilities** would also be quite useful. This could include information about sidewalks (presence, width, condition), curb ramps (presence, type), and crossings (marking type, width, length, other treatments) at both intersections and midblock. This effort would likely involve coordination between UDOT, the MPOs, and local government staff (or interns) to help collect, code, and validate this pedestrian facility information (using satellite or street-level imagery, or other sources). Obtaining this information for all roadways would be most useful, although state routes may be prioritized first.

Strava Metro data was useful, but contained some non-representativeness that was difficult to control for. Efforts should continue to find improved data source(s) for measures of **bicycle exposure**. Some promising options come from third-party providers of location-based services (LBS) data, which use mode-imputation algorithms and other processes to convert tracking data (from mobile phones, navigation systems, and apps) into travel information. Some of the companies who claim to offer pedestrian and/or bicycle volume data include StreetLight Data (StreetLight, 2020) and Replica (Replica, 2020). Given that these are third-party companies with proprietary algorithms, considerable additional research is needed to validate this data and examine its feasibility for various use cases, including as exposure for systemic safety analysis and crash modeling.

The use of **pedestrian exposure** measures derived from push-button data and measures of the built environment was very successful in this study, showcasing one of the great benefits of making these traffic signal data available. However, they were not perfect measures of pedestrian volumes, and some additional work could improve estimates, especially along segments and at non-signalized intersections. The direct-demand models (Singleton, Park, & Lee, 2021) assumed the same relationship between the built environment and pedestrian volumes at signalized intersections would also hold at all other intersections. However, exposure may be slightly overestimated at non-signalized intersections: safety barriers to crossing arterials in uncontrolled locations may funnel pedestrian traffic to signalized intersections, and the crossings that do happen at non-signalized intersections are more likely to be across the side streets rather than the main streets. Work to improve the direct-demand pedestrian volume models and validate their estimates against ground-truth count data at non-signalized intersections and along segments would help to refine pedestrian exposure measures for safety analysis.

As mentioned in the limitation section, crash records are likely underrepresenting pedestrian and bicycle crashes. Supplementing crash reports with **hospital records** and data on hospital admissions related to injuries suffered while walking and bicycling could help to fill out the picture of pedestrian and bicycle safety in Utah. However, experience in other states (e.g., Tainter et al., 2020; Hosseinzadeh et al., 2022) demonstrates the kinds of challenges that this effort would involve, including: privacy and confidentiality issues with data sharing, incomplete or incompatible records (e.g., not knowing location of incident), matching records and removing duplicates (that appear in both systems), etc.

7.1.2 Expand Data Collection of Roadway and Intersection Characteristics

The other area that would greatly improve and simplify a future systemic analysis of pedestrian and bicycle safety in Utah (or safety analysis for any mode, for that matter) would be improved and expanded collection, storage, and tracking of both roadway and intersection characteristics. As is mentioned in almost every systemic safety analysis (see Section 2.2), by far the most intensive and time-consuming effort (including for this project) is simply assembling data from various sources into one consistent data format for use in data analysis and modeling. Data about roadway, intersection, and traffic characteristics come from different sources and use different specifications, have different definitions, cover different time periods, are available for different facilities, etc. Merging them all together is challenging and involves analyst judgment based on often-incomplete information. The following efforts would help to improve data quality and make future systemic safety analyses easier and faster.

Accessing transportation GIS-based data online through platforms such as the Utah Geospatial Resource Center (UGRC) and UDOT's Data Portal (https://data-uplan.opendata.arcgis.com/) were most valuable for this study. The road-centerlines statewide dataset hosted by UGRC (https://gis.utah.gov/data/transportation/roads-system/) is an excellent resource, since it is the basis for UDOT's highway linear referencing system (and was used in this study). Continued efforts to improve the **consistency of data** from different datasets, especially the use of a consistent referencing system, would be quite useful. The segments used to define AADTs do not line up perfectly with those containing information about the number of lanes of different or the presence/type of barriers. While matching can be often be done using route and milepoint, a centralized source for all roadway characteristics could be beneficial.

More critically, most roadway and traffic characteristics information is saved as roadway segments (paths or polylines in GIS). This means that there is little to no information on **intersection locations and attributes**. As previously mentioned, in this study, intersections had to be defined as the junctions of road segments, and the attributes of intersections had to be subjectively defined based on the characteristics of adjacent/approaching segments. Creating a well-defined statewide **intersections dataset** (akin to the road centerlines dataset) and carefully crafting a standardized process to assign attributes to those intersections would generate a dataset that would be useful not just for systemic safety analysis but likely also for other tasks. This process would likely involve a collaboration between UDOT, UGRC, MPOs, and other organizations.

Many roadway characteristics in this study were only available for state routes, such as number of lanes, shoulders, medians, barriers, etc. Expanding data collection to cover **federal-aid and local routes** as well would be a big improvement and allow for safety analysis methods to include many more crashes and study locations. While potentially expensive, this may be eased through gradual efforts and collaborations involving UDOT, MPOs, counties, and cities. Centralizing this information in a statewide database with consistent field codes may even ease the burden of local municipalities to update and publish such information on a regular basis.

Finally, a challenge to the crash analyses conducted in this research project was a lack of **archived historical data** on what roadway characteristics were like at a given point in time. Rather than listing when and how such records change, it could be most useful (and easier for maintenance purposes) to simply periodically archive the up-to-date version of a particular dataset. In this way, one could potentially pull the 2017 version of lane configurations to link with 2017 crash data, but the 2012 version to link with 2012 crash data. A yearly archiving cycle may be a reasonable time frame for doing this.

7.2 Implementation Plan

The ultimate objective of this systemic analysis of bicycle and pedestrian safety is to help improve safety outcomes for people walking and bicycling on Utah roadways. To achieve this goal, the key findings and recommendations of this project need to be implemented. This implementation will require sustained efforts over several years from various stakeholders and in multiple areas. The following paragraphs detail specific elements of the recommended implementation plan.

7.2.1 Implement the Findings and Interface into Existing Tools and Procedures

As previously mentioned, this systemic safety analysis produced knowledge of risk factors, relevant countermeasures, and potential treatment locations to improve bicycle and pedestrian safety. In order to achieve the biggest benefits from this research, the project's findings and products (including the example interactive interface) should be integrated into UDOT's existing tools and procedures for roadway safety management. There are several ways in which this implementation could happen:

7.2.1.1 Develop a Safety Action Plan to Mitigate Risk Factors at High-Crash-Potential Locations

The "top-ten" locations highlighted in Section 5.4.2 show how information about historical data on observed crashes can be combined with information about risk factors from statistical models to identify locations with a high potential for future pedestrian and bicycle crashes. A safety action plan should be developed to design and implement safety countermeasures at these sites and other locations with similar characteristics. For example, several highly ranked street segments and signalized intersections overlapped and would be good candidates for an early focus on pedestrian safety:

- 3500 S (SR-171), from Mountain View Corridor to the Jordan River, West Valley City
- Redwood Road (SR-68), from 3100 S to 5400 S, West Valley City and Taylorsville
- 3300 S (SR-171), from 300 W to Highland Drive, South Salt Lake and Millcreek
- State Street (US-89), from 3300 S to 4800 S, South Salt Lake and Millcreek and Murray

These corridors all have key characteristics in common. They are all multilane arterials (2-3 thru lanes in each direction) with high traffic volumes (20,000 to 40,000 AADT). Most segments have a center two-way left-turn lane, although most of State Street and parts of 3500 S have center medians (not coincidentally, these segments with medians tended to have fewer predicted pedestrian crashes than adjacent segments without medians). These streets traverse areas with concentrations of retail and commercial land uses, often with large parking lots and many driveways, and some residential areas. Together, these characteristics imply high numbers of turning motor vehicles at intersections and also at driveways. All streets are served by frequent bus service operating every 15 minutes throughout most of the day, indicating that the presence of pedestrians is common. Speeds tend to be high: Speed limits are 35-45 mph. At those speeds, in the event of a collision between a pedestrian and motor vehicle, the risk of severe injury is high (60-90%) and the risk of death is rapidly increasing (30-60%) (Tefft, 2011). Altogether, these corridors exhibit potential pedestrian safety issues related to multiple risk factors (see Table 5.1): high pedestrian volumes, high motor-vehicle traffic volumes, arterial roadways, more travel lanes and longer crossing distances, two-way left-turn lanes, absence of medians, more driveways, more turning vehicles, and more nearby transit stops.

Given these risk factors, several countermeasures may be warranted (see Table 5.2). Corridor access management—including the use of medians, driveway consolidation, and driveway islands to provide right-in/right-out movements—could help reduce pedestrian conflicts with turning vehicles, especially for drivers turning left who may be looking for gaps in traffic but not looking for pedestrians. Medians can also help break up pedestrian crossings and are appropriate treatments for high-speed multilane arterials with speed limits 35 mph and above. Where signalized intersections are widely spaced, pedestrian hybrid beacons can be an appropriate treatment to provide controlled pedestrian crossings (especially near transit stops) while not restricting vehicle movements when pedestrians are not present. At signalized intersections with high pedestrian volumes, prohibiting right turns on red could reduce or facilitate less severe conflicts between pedestrians and right-turning motor vehicles, although driver compliance and operational impacts should also be considered. It is also important to note that many of these corridors (especially those in West Valley City) pass by neighborhoods with higher concentrations of lower-income households and people of color. This highlights the need to prioritize pedestrian safety improvements in communities that have thus far faced a disproportionate share of the burden of pedestrian collisions, injuries, and deaths.

7.2.1.2 Use Models as Bicycle and Pedestrian Safety Performance Functions

The statistical (Poisson and negative binomial) models of pedestrian and bicycle crash frequency shown in Section 4.0 are effectively safety performance functions (SPFs): They predict crashes as a function of traffic, roadway, and neighborhood context characteristics. Because they are estimated using Utah data, they are locally applicable versions of the SPFs that come from the Highway Safety Manual (HSM); they also cover more situations and variables than are in the HSM. We recommend using the A models for pedestrian crashes (these models have the most explanatory variables) and the B models for bicycle crashes (the Strava data in A might skew the findings towards recreational areas). As a result, UDOT could add them as (or replace existing) bicycle and pedestrian models in the current roadway safety management process, thus improving the capacity to estimate active transportation safety outcomes and select/evaluate projects. This work may be fairly low effort, involving UDOT Traffic and Safety staff working with Numetric to integrate the regression equations into the backend codes and processes (e.g., SPF Manager).

7.2.1.3 Update Lists of Bicycle and Pedestrian Countermeasures

The systemic countermeasures determined through past research (and summarized in Table 5.2) are linked to specific risk factors identified through the literature review and data analysis/modeling. This list could be used to enhance the existing lists of potential countermeasures that show up in the Numetric system when analyzing bicycle and pedestrian crashes. Again, this work may require less effort than other implementation tasks, likely communication between UDOT Traffic and Safety staff and Numetric to add these countermeasures to the relevant lists. Additional consideration by other UDOT units may also be necessary to ensure that the list of countermeasures would be considered desirable or feasible to implement, or if there are other challenges or considerations that should be taken into account (applicability in specific contexts, conflicts with other UDOT goals and processes, etc.) when applying a particular countermeasure.

7.2.1.4 Implement the Interactive Interface into Numetric Enhancements

The interactive interface described in Section 5.4 is just an example of what could be created. The development of a fully working and robust application was beyond the scope of this project. Such an interface would likely be most beneficial (and could probably be implemented with less cost and effort) if it were developed in tandem with existing efforts to enhance the functionality of existing safety tools, notably Numetric. As UDOT works with Numetric in their ongoing efforts to improve interactive safety management tools—either to enhance the existing Safety Analysis crash diagnosis feature, and especially to implement their version of a systemic analysis system (Predictive Analysis)—this interface could serve as an example of what could or should be developed. It demonstrates both how to combine crash models (SPFs) and historical crash data (through an empirical Bayes process) to generate better predictions of crash frequencies, as well as how to filter and rank locations to help identify countermeasures and treatment locations.

The effort to implement this would likely be substantial, but it may be diminished considering existing efforts to implement a systemic analysis component to UDOT's online tools through Numetric. UDOT Traffic and Safety staff should communicate with Numetric and ask to integrate the data, models, risk factors, countermeasures, and functionality developed as part of this research project into the enhancement efforts already underway. While a fully functioning tool may not be possible immediately, gradual enhancements could generate a product that continues to improve over a couple of years.

7.2.1.5 Refine the Interactive Interface to Add Functionality

Finally, there are many opportunities to enhance the existing interface (whether as a stand-alone tool or integrated into a Numetric Predictive Analysis system) to improve functionality and address multiple-use cases. Currently, the interface only works in a few ways: One can filter locations with specific characteristics, and/or rank sites by various safety outcomes. Other functionality may be desirable, for example: The outcome at each location could depict the marginal contribution of each risk factor towards the total predicted crash frequency, which would highlight the "biggest" risk at each location. The filtering could be done by countermeasure instead of risk factor, thus identifying locations where specific countermeasures could be useful. It may also be desirable to integrate a predictive/change element to the interface, so that it would predict how many crashes might be reduced if one or more countermeasures were implemented; this would require the addition of crash modification factors associated with each treatment. Such efforts could be implemented with a combination of smaller research projects as well as sustained efforts by UDOT Traffic and Safety and Numetric staff.

7.2.2 Implement the Data Recommendations

As detailed above, data challenges (availability, consistency, etc.) were the primary contribution to most of the study's identified limitations (see Section 6.3), leading to the data-related recommendations detailed in Section 7.1. The recommendations listed there related to bicycle/pedestrian data—improvements in data collection on pedestrian-related facilities, measures of pedestrian and especially bicycle exposure, and integration of hospital injury records—as well as roadway/intersection data—improving data consistency, intersection locations and attributes, coverage of local roads, and historical archiving—should be pursued. These efforts would improve knowledge of current conditions as well as improve future systemic analyses related to bicycle and pedestrian safety.

This work could be led by staff from UDOT's Traffic and Safety Division, with additional resources and involvement of UDOT Planning, the Utah Department of Public Safety (DPS) Highway Safety Office (HSO), and the Utah Geospatial Resource Center (UGRC), as well as MPO/county/city staff and potentially consultants. Some efforts (like improving measures of bicycle exposure or the integration of hospital records) may require additional research projects. Other efforts (like data on pedestrian facilities, an intersection's dataset, or data archiving) are best led or conducted internally, by existing (or new) staff and/or intergovernmental working groups. Some work may be able to be completed more quickly (e.g., pedestrian facilities, data archiving), while other tasks will likely require work over multiple years to be implemented (e.g., hospital records, information on local roads).

7.2.3 Repeat this Systemic Analysis Periodically

Finally, systemic safety analysis is not a product but a process. While this analysis made use of ten years of data and sophisticated modeling to generate findings and recommendations (risk factors, models, countermeasures, etc.), it will gradually become out of date as additional efforts are made to improve bicycle and pedestrian safety in Utah, and as trends evolve and new traffic safety concerns come to the forefront. Therefore, this systemic analysis of bicycle and pedestrian safety should be repeated on a periodic basis. There are no strong guidelines on how frequently a systemic analysis should be replicated, although a 5-to-7-year cycle seems reasonable.

Since this effort has already been done once, it should be slightly easier, faster, and cheaper to conduct again in the future. This case will be made stronger if some of the data improvement recommendations are implemented. When the next systemic analysis of bicycle and pedestrian safety in Utah is conducted, it could be useful to also slightly improve the methods utilized. For instance, machine-learning methods such as gradient-boosted decision trees (see Section 6.3) could help to identify risk factors and non-linear relationships prior to estimating more conventional crash frequency regression models. Hopefully the next effort will improve upon some of this study's limitations to produce a systemic analysis that continues to aid in efforts to improve safety outcomes for people walking and bicycling in Utah.

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