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SYSTEMIC PEDESTRIAN SAFETY ANALYSIS: CONTRACTOR'S TECHNICAL REPORT

Prepared for:

National Cooperative Highway Research Program
Transportation Research Board

of

The National Academies of Science, Engineering, and Medicine

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CONTENTS

ACKNOWLEDGEMENT OF SPONSORSHIP i
DISCLAIMER i
LIST OF TABLES..... v
LIST OF FIGURES.....vi
LIST OF ACRONYMS.....vii
AUTHOR ACKNOWLEDGEMENTS ix
ABSTRACT x
SUMMARY 1
Key Research Tasks 1
Key Research Findings..... 2
CHAPTER 1: State of Systemic Pedestrian Safety Practices in the U.S. 5
1.1 Research Methods 5
1.2 Research Findings..... 6
1.3 Key Takeaways 13
CHAPTER 2: Data for a Systemic Pedestrian Safety Analysis 16
2.1 Data for Systemic Pedestrian Safety Process 16
2.2 Complementary Data Sources and Processes 26
2.3 Data Limitations in Practice..... 30
2.4 Implications for Systemic Processes..... 33
CHAPTER 3: Summary of Literature on Risk Factors and Systemic Risk Analysis 34
3.1 Summary of Pedestrian Risk Factors 34
3.2 Risk Analysis Method Rationale and Considerations..... 42
CHAPTER 4: Research to Develop New Risk Factors 45
4.1 Background 45
4.2 Research Methods 48
4.3 Results and Discussion 56
4.4 Summary and Implications for Systemic Pedestrian Safety Process 65
CHAPTER 5: Identifying Systemic Pedestrian Countermeasures 68
5.1 Research Methods 68
5.2 Systemic Countermeasure Selection Criteria 69
5.3 Other Effectiveness and Implementation Considerations..... 71
CHAPTER 6: Discussion and Future Research Needs..... 73
REFERENCES 75
APPENDIX A: Survey on Systemic Practices 82

Survey Questions 82
Summary of Survey Responses 84
APPENDIX B: Results of Prior Crash Frequency and Severity Studies Reviewed 88
APPENDIX C: Risk Factors with Positive or Negative Associations with Pedestrian Crash Severity by Location Types 101

LIST OF TABLES

Table 1. Roadway inventory data. 17

Table 2. Motorized traffic data. 18

Table 3. Non-motorized traffic data. 20

Table 4. Transit data. 22

Table 5. Land use data. 23

Table 6. Socioeconomic data. 24

Table 7. Pedestrian crash data. 25

Table 8. Roadway safety audit data and processes. 27

Table 9. User surveys and other public input. 29

Table 10. Pedestrian crash and injury risk factors identified in existing literature. 34

Table 11. Variables associated with increasing (+) or decreasing (-) pedestrian crash frequency in a specific model. 38

Table 12. Variables and categories associated with increasing (+) or decreasing (-) pedestrian crash severity. 42

Table 13. Summary of variables available for analysis and the source. 49

Table 14. Overlap of the two analyzed collision types. 51

Table 15. Descriptive statistics of scalar variables tested in models. 52

Table 16. Descriptive statistics of categorical variables tested in models. 53

Table 17. Final model statistics for crashes between motor vehicles traveling straight striking pedestrians on segments (PMV_strt), and crashes under dark conditions on segments (PedDark). 61

LIST OF FIGURES

Figure 1. ActiveTrans Priority Tool methodology (Figure 1 in Lagerwey et al. 2015). 10

Figure 2. NCDOT Flow Chart for Step 1 (Schroeder et al. 2015). 13

Figure 3. CRF variable importance for PMV_Strt model. 58

Figure 4. CRF variable importance for PedDark model. 59

Figure 5. Spreadsheet showing some observed values for significant factors and predictions for PMV_Strt pedestrian crashes at specific segments. 66

LIST OF ACRONYMS

AADB	Average Annual Daily Bicycle Traffic
AADP	Average Annual Daily Pedestrian Traffic
AADT	Average Annual Daily Traffic (Motor Vehicles)
AASHTO	American Association of State Highway and Transportation Officials
ADT	Average Daily Traffic
AIC	Akaike's information criterion
ASE	Automated Speed Enforcement
BIC	Bayesian information criterion
Caltrans	California Department of Transportation
CMF	Crash Modification Factor
CRF	Conditional Random Forest
CURE	Cumulative Regression
DCMF	Development of Crash Modification Factors Program
DOT	Department of Transportation
EB	Empirical Bayes
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
GIS	Geographic Information System
HSIS	Highway Safety Information System
HSM	*Highway Safety Manual*
IAP	Intersection Action Plan
MMIRE	*Model Minimum Inventory Roadway Elements*
MPH	Miles Per Hour
MPO	Metropolitan Planning Organization
MUTCD	Manual on Uniform Traffic Control Devices
NB	Negative Binomial
NBPDP	National Bicycle and Pedestrian Documentation Project
NCDOT	North Carolina Department of Transportation
NCHRP	National Cooperative Highway Research Program

NHTS	National Household Travel Survey
NHTSA	National Highway Traffic Safety Administration
ODOT	Oregon Department of Transportation
PBCAT	*Pedestrian and Bicycle Crash Analysis Tool*
PBISI	*Pedestrian and Bicycle Intersection Safety Indices*
PCS	Pedestrian countdown signals
PEDSAFE	*Pedestrian Safety Guide and Countermeasure Selection System*
PEDSMARTS	*Pedestrian Systemic Monitoring Approach for Road Traffic Safety*
RSA	Road Safety Audit
SafeTREC	Safe Transportation Research and Education Center
SDOT	Seattle Department of Transportation
SPF	Safety Performance Function (i.e., crash prediction model); see glossary for definition
TAZ	Traffic Analysis Zone
TCRP	Transit Cooperative Research Program
TDOT	Tennessee Department of Transportation
TIGER	Topologically Integrated Geographic Encoding and Referencing
TMAS	Federal Travel Monitoring Analysis System
TRB	Transportation Research Board
TRID	Transport Research International Documentation
TRIS	Transportation Research Information Services
TWLTL	Two-way Left Turn Lane
UNC-HSRC	University of North Carolina Highway Safety Research Center

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ABSTRACT

The objective of this research was to develop a process, detailed in the *Systemic Pedestrian Safety Analysis Guidebook*, for (1) conducting systemic pedestrian safety analysis using robust analytical techniques to identify roadway features and other risk factors to consider in a systemic pedestrian safety process; (2) identify appropriate and cost-effective systemic pedestrian safety improvements to address the associated risk factors; and (3) enable transportation agencies to prioritize candidate locations for selected safety improvements based on risk. To develop the process and related Guidebook, the team performed the following key tasks: (1) conducted a literature review and practitioner interviews to identify systemic processes used by agencies; (2) identified data needs and sources for a robust systemic pedestrian assessment; (3) compiled risk factors (associated with pedestrian crash frequency and/or severity) from published analyses; (4) conducted negative binomial regression analysis of a network-wide database to identify risk factors associated with pedestrian collisions occurring at segments and to demonstrate an analysis approach; (5) reviewed and identified a select set of candidate pedestrian crash countermeasures compatible with systemic processes; and (6) developed case examples describing real or hypothetical applications of a robust systemic pedestrian safety process.

SUMMARY

The objective of this research was to develop a process and guide for (1) conducting systemic safety analyses for pedestrians using analytical techniques to identify pedestrian activities, roadway features, and other contextual and behavioral risk factors, such as land use, that increase pedestrian crashes; (2) identifying appropriate and cost-effective systemic pedestrian safety improvements to address the associated risk factors; and (3) enabling transportation agencies to prioritize candidate locations for selected safety improvements based on risk. The research results should aid transportation agencies in more effectively allocating resources for pedestrian safety improvements that will reduce risks for future crashes at many locations across a network.

This final Technical Report is intended to serve as a companion to the program manager and practitioner-oriented *Systemic Pedestrian Safety Analysis Guidebook* (Guidebook), offering the research background, and additional technical details on data sources, variables, and analysis methodologies that may be useful to some agencies for implementing the process. The research community and other stakeholders may also find useful information detailing prior research and continuing research needs.

Key Research Tasks

To develop the process and related *Systemic Pedestrian Safety Analysis Guidebook* (Guidebook), research was needed to (1) identify and describe a robust systemic, pedestrian safety analysis process, (2) identify key pedestrian risk factors and the underlying data sources needed to identify pedestrian crash risks across a roadway network, and (3) identify and provide guidance on analysis methods, countermeasure applications, and prioritization in a systemic process. The research was completed through the following key tasks:

- Task 1: Conduct a literature review and perform focused interviews with practitioners to identify general systemic processes and the overarching steps used by agencies in the U.S. (pedestrian and non-pedestrian focused) and define key terms or concepts in a systemic approach;
- Task 2: Identify data needs and sources for a robust systemic pedestrian assessment;
- Task 3: Compile risk factors (associated with pedestrian crash frequency and/or severity) from published analyses;
- Task 4: Conduct original analysis using an available network-wide database to identify additional risk factors associated with two types of pedestrian midblock collisions;
- Task 5: Review and identify a select set of candidate pedestrian crash countermeasures compatible with systemic processes; and
- Task 6: Develop case examples describing real or hypothetical applications of a robust systemic pedestrian safety process.

The following chapters summarize this research, which in turn informed the development of the *Systemic Pedestrian Safety Analysis Guidebook*.

- Chapter 1 summarizes the literature review and state of practice identified through a survey and follow-up interviews conducted with agencies on their systemic safety processes (Task 1);
- Chapter 2 describes data to consider for systemic pedestrian safety analysis and sources for those data (Task 2);
- Chapter 3 describes the findings from the detailed risk-related review (Task 3) of prior research and incorporates findings from the Task 4 analysis described in Chapter 4;

- Chapter 4 describes analyses (Task 4) conducted to supplement knowledge of risks associated with segment-related pedestrian collisions;
- Chapter 5 describes the work performed in Task 5 to identify a potential list of systemic pedestrian crash countermeasures, and to develop criteria and a process for selecting such countermeasures; and
- Chapter 6 provides a discussion of the overall findings from the research process, and outlines additional research needs to enhance and further develop systemic approaches to pedestrian safety.

The case examples that were developed in Task 6 are included in the *Systemic Pedestrian Safety Analysis Guidebook.*

Key Research Findings

Major research findings (further described in each Chapter) include:

The research documented in **Chapter 1** found that practitioners applied varying definitions of the systemic process, that many agencies faced challenges in implementing robust systemic processes due to a lack of pedestrian volume data, roadway features information, and other data needed for analysis. The research team developed a working definition of a risk-based, systemic approach as follows:

> *A systemic approach is a data-driven, network-wide (or system-level) approach to identifying and treating high-risk roadway features correlated with specific or severe crash types. Systemic approaches seek not only to address locations with prior crash occurrence, but also those locations with similar roadway or environmental crash risk characteristics.*

Based on the review of current practices and agency interviews, the research team defined several needs for a systemic pedestrian safety analysis process, including a need to: better define the systemic process, provide robust analysis methods while still accounting for data limitations, provide a summary of risk factors from prior research, identify effective lower-cost countermeasures, and provide guidance to support agency decision-making during a systemic process. These needs provided further impetus for the work performed in Task 2 and beyond, and which is documented in subsequent chapters.

In **Chapter 2**, the team documented types of data available and useful for systemic safety analysis including roadway, facility types, and operations; motorized traffic data; non-motorized or pedestrian and bicycle traffic data. Other less traditional types of data were also identified that have made important contributions to understanding pedestrian crash risks. These included transit-related variables, population (socio-demographic), and land use variables. Land use, transit, and demographic data have been found to serve important functions in a systemic pedestrian safety analysis: 1) these measures may provide approximations for risks associated with the complexity of the pedestrian environment, pedestrian activities, and behaviors on the roadway network that are challenging to measure more directly (reflecting the very different ways that pedestrians use and access roadways compared to motorized traffic); and 2) they may also serve as partial approximations for pedestrian or traffic volume data when these measures are incomplete or unavailable. The information presented in this chapter includes examples of jurisdictions that have collected and analyzed these data types, and descriptions of studies conducted with alternate methods and various types of data.

Chapter 3 describes key pedestrian risk factors identified from prior studies and from the analysis of midblock pedestrian collisions described in Chapter 4. The literature verified the importance of accounting for traffic and pedestrian volumes (often referred to as exposure) and using network-wide data to identify additional pedestrian crash and injury risk factors. Variables that are often associated with pedestrian crash potential were characterized according to location types (primarily urban and suburban intersections and segments) by reviewing 25 analytical studies of pedestrian crash frequency. Reviews of crash severity supplemented the list with variables associated with greater tendency for fatal and severe injury when crashes occur. This review, combined with analyses for this project, identified key variables that agencies should consider collecting and analyzing in assessments of pedestrian crash risk. Some of the key variables associated with pedestrian crash frequency include the following:

- Motorized vehicle traffic volume;
- Pedestrian volume;
- Measures of urban density and land uses;
- Transit measures;
- Number of traffic lanes;
- Speed limit;
- Striped or metered parking presence;
- Commercial driveway presence or density;
- Median/median island presence;
- Turn restriction phasing at signalized locations;
- At Intersections: number of legs, traffic control type, right or left turn lanes; and
- At Segments: segment length, presence of uncontrolled crosswalks, presence of two-way left turn lane (TWLTL).

Chapter 3 also provides rationale for the risk analysis method recommended in the Guidebook (a crash frequency, model-based approach), including the benefits and limitations of different methods and key considerations relevant for a systemic approach to safety. Borrowing from the traditional highway safety practice, the method of developing safety performance functions (SPFs) was identified as a valuable analysis approach to identify crash risk factors, and for use in screening and prioritization.

Chapter 4 describes the analyses conducted to supplement knowledge of risks associated with midblock (segment-related) pedestrian collisions and demonstrated the application of the recommended analysis approach. Using network-wide data for all segments from Seattle, Washington, crash prediction factors were identified for crashes involving pedestrians crossing at midblock locations who were struck by motor vehicles traveling straight. A second analysis included all types of pedestrian collisions that occurred at night at segment locations (PedDark). The analyses identified variables that other agencies may consider for collection and analysis, and the results provide inputs for examples of different steps in the Guidebook.

Chapter 5 describes the criteria to consider in developing a framework for selecting countermeasures for systemic application. The criteria include: safety effectiveness, cost, and feasibility. A select set of pedestrian crash countermeasures were identified using these criteria, which agencies could consider including in their own systemic safety programs. The Guidebook provides more information about 12 countermeasures, including the risks and crash types that might be targeted, the effectiveness evidence, and the location characteristics where the countermeasures may be most applicable.

Chapter 6 provides a brief discussion of the current state of systemic pedestrian safety and some of the key challenges and issues that remain unresolved, or where more research could shed light. Certain agencies have led the way in beginning to compile, estimate, and otherwise develop robust datasets and use robust analysis methods to identify and prioritize pedestrian safety needs on a systemic basis.

However, additional research is needed on methods of approximating exposure and better capturing certain types of risk (behaviors and environmental factors at the time of the crash). Such methods may help to improve the depth of knowledge and understanding of which countermeasures are most likely to work and where. Additional safety research studies are needed in the future to quantify the crash effects of more treatments, such as curb extensions and other sight distance improvements near crossings, and other lower cost operational treatments such as right-turn-on-red restrictions and other signing measures. Such studies to generate crash modification factors (crash-based safety effects) would be useful for informing systemic pedestrian safety processes and proactive pedestrian facility designs.

In time, systemic applications of treatments across many jurisdictions may offer new opportunities to evaluate crash effects of different treatments. Agencies can assist in this process by providing proper documentation (i.e., specific location and date of implementation, treatment description) of projects, with data linkable by locations and time. For individual agencies, it will also be important to monitor systemic program implementation and note successes and challenges that could be addressed to improve a systemic process over time.

CHAPTER 1: State of Systemic Pedestrian Safety Practices in the U.S.

This chapter provides an overview of the state of practice in applying a systemic pedestrian safety analysis process in the United States and identifies gaps and deficiencies in the process as it currently exists. This information was synthesized by reviewing relevant literature, and by gathering input from practitioners and traffic safety professionals through an online survey (see Appendix A for survey questions and a summary of responses). It also includes conducting phone interviews with select transportation agencies throughout the U.S. that were identified as having promising systemic or partially systemic practices.

1.1 Research Methods

ELECTRONIC SURVEY

The research team conducted an electronic survey to solicit input from traffic safety professionals on the issues and challenges associated with applying systemic safety approaches to the planning, analysis, and development of systemic solutions for pedestrian safety. The two main objectives of this were to:

1. Identify projects or studies in which systemic pedestrian safety improvement techniques may have been applied; and
2. Develop a better sense of the current state of the practice relative to the implementation of systemic pedestrian safety improvements.

Rather than designing the electronic survey to collect detailed information on these objectives, the survey was used as a "spotter" to surface projects that the research team could then explore further with the respondents (using their contact information). As such, it was broadly circulated and intentionally brief.

The survey was distributed to many targeted stakeholder groups that were known to have a strong interest in pedestrian safety (e.g., TRB Committees, AASHTO Standing Committee on Highway Traffic Safety, and Traffic Safety leaders from DOTs). Respondents were asked for information regarding the scope and nature of their systemic safety practices, as well as their level of personal involvement. An open comment section allowed respondents to provide a summary of their practices, as well as links to additional documentation. In this regard, the survey was used to identify organizations and projects where systemic practices may have been applied. Based on this information, the research team was able to further investigate these potential applications by conducting in-depth phone interviews with the respondents.

In a period of seven weeks, there were 98 responses to the survey. Respondents ranged from safety practitioners at state and city DOTs to safety researchers at universities to traffic safety consultants. A summary of the survey and responses can be found in Appendix A of this report. A few takeaways from the survey responses include:

- There were various working definitions of "systemic" safety practices in use throughout all levels of transportation community. Although most practitioners responding to the survey indicated that they had been involved in systemic safety improvements, many of those appeared to be corridor safety improvements, categorical safety improvements or traditional hotspot analyses. As a result, only a few survey respondents were targeted for follow-up interviews.
- There were elements in some of the projects that included what this study would define as systemic; however, none of the projects demonstrated a truly integrated systemic process involving needs assessment, identification of risk factors, prioritization of needs, and countermeasure selection.

PRACTITIONER INTERVIEWS

Based on the survey responses, the research team identified and performed follow-up interviews with a few key state and local agencies. These agencies were identified as meeting one of the following criteria:

- They were known to be applying advanced pedestrian safety practices;
- Their work was referenced in the literature (see next section); or
- The agency responded to the electronic survey and responses merited follow up.

While not exhaustive, the list of agencies interviewed represents a targeted group who held the most potential for revealing the state of the practice with regards to systemic pedestrian safety practices.

LITERATURE REVIEW

The findings of the literature review also supported the research team in identifying opportunities to improve the use of systemic methods for pedestrian crash analysis by state and local agencies. The literature included prior and ongoing NCHRP projects, and project work conducted by state and local agencies. The literature was identified through input from the project team, the project panel, DOT staff, and other professionals. The literature review was supplemented by input gathered from state and local agencies through the online survey and phone interviews.

1.2 Research Findings

The surveys, interviews, and literature review tasks described in Section 1.2 resulted in documentation of the following research findings, which are further described in the sections below:

- Systemic Methodologies;
- Example Applications.

Literature and interview findings related to data and data limitations, risk factor identification, and pedestrian crash countermeasures are described in the relevant chapters (Chapters 2, 3, and 5).

SYSTEMIC TOOLS AND METHODOLOGIES

Three published systemic methodologies developed by reputable agencies are summarized in the following subsections. The methodologies vary in scope, one applying to a comprehensive systemic safety process, and two reflecting network screening and priority site selection. Each is presented as an example of a systemic method that could be applied or adapted to address pedestrian crash risk.

Systemic Safety Project Selection Tool

The FHWA developed the *Systemic Safety Project Selection Tool* to document a comprehensive systemic safety method applicable to multiple crash types and settings (Preston et al. 2013). Additionally, some state and local agencies have developed their own variations of a systemic method to match available data, meet their agency's needs, or to address a specific crash type. This section describes the basic premise of the systemic method, as described by the *Systemic Safety Project Selection Tool*, and summarizes how other agencies have developed variations of the method.

The *Systemic Safety Project Selection Tool* provides practitioners with a step-by-step approach for conducting systemic safety analysis, as well as analytical techniques for quantifying the benefits of a systemic program. The basic tenets of a systemic safety process are that it:

- Identifies a safety concern based on an evaluation of data at the system-level;

- Establishes common characteristics (risk factors) of locations where severe crashes frequently occur;
- Emphasizes low-cost safety countermeasures to address the underlying risk factors identified; and
- Prioritizes locations across the entire roadway network where risk factors are present, regardless of prior crash history.

The successful implementation of a systemic planning process requires the evaluation of the entire system based on the identified risk factors. The basic framework of the systemic planning process, as developed for the *Systemic Safety Project Selection Tool*, is as follows:

Element 1:

- Identify Focus Crash Types and Risk Factors;
- Screen and Prioritize Candidate Locations;
- Select Countermeasures; and
- Prioritize Projects.

Element 2

- Identify Funding for Systemic Program and Implement.

Element 3

- Perform Systemic Program Evaluation.

FHWA's *Systemic Safety Project Selection Tool* offers two approaches to evaluate potential risk factors.

1. Use descriptive statistics to compare the number of locations where the risk factor exists and the percentage of the focus crash type occurring at these locations. If a high proportion of such crashes occur at locations with a relatively rare roadway characteristic (e.g., skewed intersection), it may represent a useful risk factor.
2. Review roadway characteristics using crash modification factors (CMFs) from research or other databases and identify roadway elements (or lack thereof) shown to have a positive effect on particular crash types. Risk factors can be selected with relative confidence that they represent an increased crash potential (Preston et al. 2013). The strength and applicability of the CMF and other risk-related research should be evaluated carefully before making this determination.

Both systemic approaches require a minimum amount of data to identify factors associated with increased risk. Many agencies currently do not have the minimum data needed to apply either method to assess pedestrian crashes, such as a detailed inventory of facilities.

The systemic methods outlined in the *Systemic Safety Project Selection Tool* do not necessarily use analysis methods that account for randomness of crash locations or control for other factors present to determine the risk factors directly associated with increased risk for various crash types. The methods used may simply identify factors associated with high crash frequencies at particular locations and may improperly assume a correlation with a particular factor present at the location. This may result from several issues, including random elements associated with high crash occurrence, or associations with large exposure or other underlying causes that are either not measured or have not been identified. Accounting for pedestrian exposure in analyses would be an important aspect of a systemic pedestrian safety process, especially since risks may be high at locations where relatively few people may be walking, and crashes may be relatively infrequent.

The *Highway Safety Manual* (HSM, 2010) and other research stresses the importance of accounting for traffic volume and other potential risk factors in safety analyses. Unless pedestrian and motor vehicle volumes are included in analyses of system or network data, the other risk factors identified may be misleading and result in less than ideal prioritization of resources.

Pedestrian and Bicyclist Intersection Safety Indices

University of North Carolina Highway Safety Research Center (UNC-HSRC) developed a methodology for FHWA that rates intersections based on their relative risk to pedestrians and bicyclists. The methodology is based on observable roadway characteristics (Carter et al. 2007). This methodology was developed as a proactive method to screen for "higher-risk" intersections for pedestrians or bicyclists.

Models were developed that used intersection characteristics to predict 1) expert safety ratings of each crossing, and 2) conflicts and maneuvers (considered proxies for safety) during interactions of pedestrians and motorists at each crossing. There were insufficient crashes to develop crash-based models. Descriptive factors for each of 68 pedestrian crossings at intersections were coded; descriptors included geometric characteristics, predominant land use around the intersection, and traffic volumes and speeds. Video data were recorded for each crosswalk and were subjectively rated for comfort and safety (using a data collection instrument) by traffic safety engineers, planners and other pedestrian safety professionals. In addition, hundreds of hours of video data of motor vehicle and pedestrian interactions were recorded, extracted, coded, and analyzed. In total, 1,095 pedestrian-motorist interactions (conflicts and evasive maneuvers) were used in the analysis. Models of the subjective ratings and models of the behavioral data (conflicts and evasive maneuvers) were developed using the characteristics of the intersection approaches and crossings and the model results were compared. Many of the same risk factors were identified in both model types.

All of the significant factors in the (expert) ratings model were ultimately retained in the pedestrian and bicycle intersection safety indices (PBISI) models. Therefore, while the tool is not crash-based, the inputs included safety-related behavioral data and user interactions and conflicts as well as expert-judgment data from review of videotaped observations. Factors used in the final ISI procedure included the intersection characteristics associated with greater perceived risk as rated by the safety experts. The significant model characteristics have also been found to be associated with pedestrian crash risk in other safety analyses. High-risk roadway variables included in the final ISI model include: presence/absence of traffic signal; presence/absence of stop control on street being crossed; number of thru lanes on the street being crossed; 85th percentile speed of street being crossed; traffic volume on the street being crossed; and predominant land use (i.e., commercial or non-commercial land use).

A 6-point ISI rating scale was developed based on the roadway features found to be important risk factors. The index is calculated for each pedestrian crossing at an intersection. A rating of 1 or 2 represented a very low-risk crossing (e.g., two-lane road with low vehicle speeds and volumes) and a 5 or 6 was considered a high-risk situation (e.g., multi-lane road with high vehicle speeds and volumes). The factors that were associated with greater risk in the pedestrian index included:

- Intersection does not have a traffic signal (with pedestrian signal);
- Intersection does not have a stop sign;
- Higher number of lanes (maximum of four lanes for applicability of ISI);
- Higher vehicle speed limits (maximum of 45 mph for applicability of ISI);
- Higher traffic volume (maximum of 50,000 vehicles per day for applicability of ISI); and
- The land use is in a predominately commercial area.

Spreadsheets are available for agencies to easily calculate the risk indices for intersection crossings. The PBISI also requires data that may need to be collected including traffic volume, speed limits, and traffic control type. This tool is considered a first step that allows users to identify intersection crossings that may be priorities for more in-depth pedestrian safety assessments. Nabors et al. (2009) combined PBISI values from each crossing to create a single index value per intersection and found that the index ratings correlated well with user perspectives of risk when they applied the tool to screen crossings in a rail transit improvement area.

ActiveTrans Priority Tool

NCHRP developed the ActiveTrans Priority Tool to help agencies effectively prioritize and implement pedestrian and bicycle projects (Lagerwey et al. 2015). Using a data-driven methodology, the tool facilitates an understanding of the prioritization process in a manner that fosters transparency. However, it is not intended to provide any guidance on potential countermeasure selection.

Figure 1 shows the methodology behind the tool; ActiveTrans is broken down into two distinct phases and ten steps. After utilizing the tool, agencies should hold a ranked list of pedestrian and bicycle improvement locations that were the result of a data-driven and objective analysis.

An important aspect of this approach is that safety is one of nine factors suggested for consideration when prioritizing projects. Other important factors include demand, public input, and opportunity (e.g., making pedestrian facility improvements as a part of roadway reconstruction or repaving projects). Therefore, agencies can use the tool to take a broad perspective toward prioritizing pedestrian projects and weight safety concerns relative to other important planning considerations. The ActiveTrans Priority Tool Guidebook suggests variables such as reported bicycle and pedestrian crashes, proportion of pedestrians walking in the roadway, and proportion of pedestrians complying with “Don’t Walk” signals to represent safety, but these are not necessarily based on existing data types or analysis of risks across one or more networks. This tool may, however, complement a systemic pedestrian safety process by helping an agency complete the prioritization steps for systemic projects in a well-documented manner.

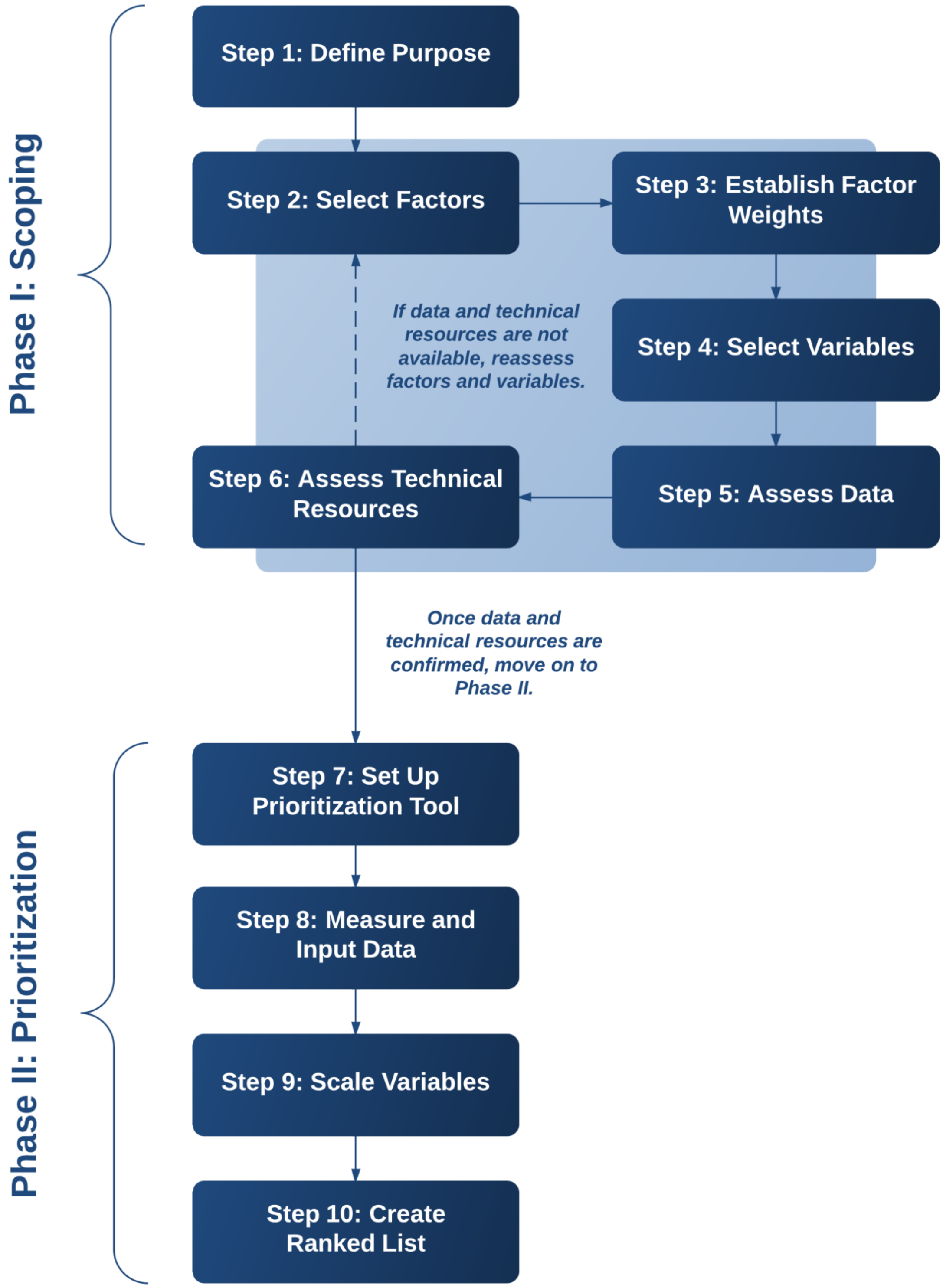

Figure 1. ActiveTrans Priority Tool methodology (Figure 1 in Lagerwey et al. 2015).

EXAMPLE APPLICATIONS OF SYSTEMIC ANALYSIS METHODS

The research team took a broad look at practices and examples that agencies felt demonstrated systemic approaches to pedestrian safety. Some agencies were employing practices that they felt were "systemic" including a corridor approach to treatment or identifying a certain countermeasure and searching for locations that may benefit from application of that measure. These methods may be partially systemic and may be useful approaches to pedestrian safety if carefully applied, but they are not necessarily based on an analysis of factors that increase pedestrian crash risk across the network. The following subsections present several case examples demonstrating the use of systemic analysis and screening throughout the United States. The example applications are classified based on how risk factors were identified, as one of the following methods:

1. Systemic risk analysis based on empirical methods;
2. Systemic risk assessment based on risks from prior studies;
3. Systemic risk analysis based on crash frequencies subset by a pre-determined set of factors; or
4. Systemic risk assessment based on expert or stakeholder opinion (e.g., local ad-hoc methods).

In addition, some agencies have developed their own countermeasures decision guides, which could be useful tools for a systemic process. One example of this type is featured below, although others exist.

Systemic Risk Analysis Based on Empirical Methods

SDOT conducted a citywide Bicycle and Pedestrian Safety Analysis, which represents one of the most relevant example of a comprehensive, data-driven evaluation of pedestrian and bicycle crashes using a systemic method conducted in the US prior to 2016. In this work for SDOT, a team developed SPFs for two types each of pedestrian and bicycle crashes at intersections. SDOT used the resultant model-based predictions to further systemic, risk-based treatment implementations. Initial screening was used to identify higher-risk signalized intersections. Observations (field diagnosis) revealed conflicts with turning vehicles that could benefit from leading pedestrian intervals in the phasing. SDOT also consults risk-based rankings from model-derived crash predictions (EB-estimated or SPF-predicted crashes) to ensure pedestrian needs at higher predicted risk locations are considered in all types of projects. This effort and other examples of systemic or partially systemic processes identified below are featured in more detail in the Guidebook.

In an earlier study SDOT staff performed an assessment and inventory of midblock crossing locations. The team used the results from a multi-jurisdictional safety analysis of uncontrolled crossings (by Zegeer et al. 2005) to identify uncontrolled crosswalks that may need further safety improvements based on conditions such as number of lanes, traffic volume and speed (see case example in Thomas et al. 2016).

Oregon Department of Transportation (ODOT) conducted a statewide systemic safety analysis to identify locations with the highest risk of a pedestrian or bicycle crash to inform the Oregon Pedestrian and Bicycle Safety Implementation Plan. In this example, risk analysis and screening were performed to identify potential improvement locations. To aid in prioritization of 0 to low crash sites, the HSM crash-prediction methodology was used to generate crash estimation metrics.

Systemic Risk Analysis Based on Risks from Prior Studies

The 2017 update of the Arizona Pedestrian Safety Action Plan (PSAP) is another example of development and use of a systemic pedestrian safety process to complement a high-crash approach to identify, prioritize, and select sites for review and possible improvement by a state DOT. In addition to identifying sites with concentrations of pedestrian crashes on the Arizona state highway system, it was understood that some locations had high-risk characteristics that were similar to locations where pedestrian crashes had occurred. Therefore, a systemic process was developed using data already available in the state's roadway database. Roadway and socio-economic data variables were selected which were known from the safety literature to be associated with high risk for pedestrian crashes. An economic analysis methodology was also developed that bundled high-risk sites with high crash sites proposed for the same treatments since high-risk sites were unlikely to be competitive for safety improvement funds on their own.

Systemic Risk Analysis Based on Crash Frequencies by Roadway Location Factors

To help compliment their traditional hotspot analysis, the California Department of Transportation (Caltrans) has developed a screening approach to identifying high-risk locations (Grembek et al. 2013). The approach, dubbed the Pedestrian Systemic Monitoring Approach for Road Traffic Safety (PEDSMARTS), focuses on developing strategies to reduce pedestrian and bicycle injuries along urban arterials. Caltrans sought to use this program as a means for more effectively incorporating pedestrian and bike projects into their safety funding, as these users were typically underrepresented through traditional hotspot analyses due to lack of exposure.

Systemic Risk Analysis Based on Expert or Stakeholder Opinion (e.g., Local Ad-Hoc Methods)

Tennessee Department of Transportation (TDOT) developed the Intersection Action Plan (IAP) Safety Initiative, which applied a systemic safety planning process to stop-controlled intersections. Intersection safety has been identified as an emphasis area in Tennessee's State Highway Safety Plan since 2004, so using it as means to identify risk factors was inherent. With guidance from FHWA Division staff and the FHWA Report Low-Cost Safety Enhancements for Stop-Controlled and Signalized Intersections (FHWA-SA-09-020), TDOT was able to identify several common risk factors associated with stop-controlled intersections (e.g., pavement and lighting conditions, sight distance, intersection geometry) and developed a list of potential countermeasures to combat fatal and serious injury crashes across the state roadway system. The IAP Procedure Manual was developed from this safety initiative and provides step-by-step procedures for practitioners to apply for systemic safety improvement funding at unsignalized intersections.

Site-Specific Risk Assessment and Countermeasures Selection Process

In April of 2015, North Carolina Department of Transportation (NCDOT) proposed a Pedestrian Crossing Guidance Flow Chart. This method incorporates risks identified from prior research studies—in particular the Zegeer et al. (2005) crosswalk study and NCHRP Report No. 562 (Fitzpatrick et al. 2006)—with state guidance and Manual on Uniform Traffic Control Devices (MUTCD) considerations into a decision guide that can be used to help determine appropriate treatments for pedestrian crossings. The North Carolina Guide covers both controlled and uncontrolled of crossing locations, but focuses most attention on uncontrolled crossings (Schroeder et al. 2015). School-crossings and bicycle-path crossings are not covered.

The result was a flow chart process to be used for a variety of purposes (e.g., citizen or municipal request, high crash location), but could also be used as part of systemic process to select risk-based and context-based appropriate countermeasures. Important data variables to be gathered at crossing locations are traffic volume, speed limit, operating speed, quantity and type of pedestrian activity, pedestrian crash history, roadside features and conditions, area factors, and signing or other traffic control device options. The flow chart is broken up into four steps and is supplemented with a 95-page guide.

Each step focuses on a different crossing location type, with a flow chart process to determine if improvements are warranted or no action is needed. Figure 2 illustrates the flow chart portions for Step 1, which focuses on decision criteria for signalized crossings. This serves as an example of a decision-guide that agencies might consider developing to assist with prioritizing countermeasures for systemic application, relevant to their location context.

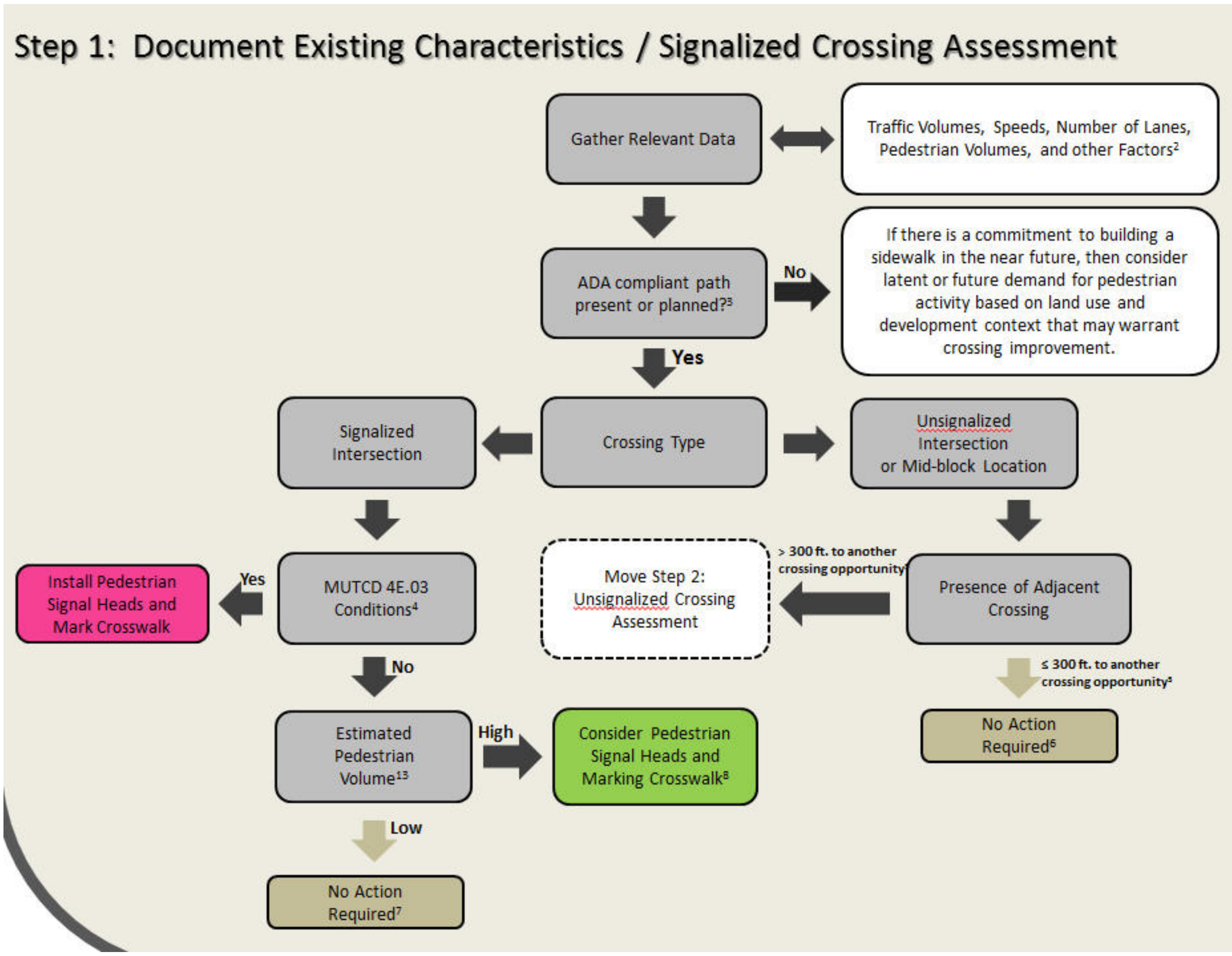

Figure 2. NCDOT Flow Chart for Step 1 (Schroeder et al. 2015).

1.3 Key Takeaways

The following key findings from the literature review and practitioner interviews informed the Guidebook development in several ways:

- **Need to define the process** – Not every interview evidenced the use of systemic practices; however, several agencies highlighted their desire to move towards systemic analysis. Perhaps the most important conclusion from the interviews was the multiplicity of working definitions of "systemic" safety practices. The Guidebook aims to build a common vocabulary around systemic practices by providing a definition of "systemic" principles, glossary of key terms, a step-by-step process, and a range of real-world examples that show systemic and quasi-systemic processes. Since the research team was tasked with developing a risk-based approach to systemic pedestrian safety, we developed a working definition to apply in the guidance. The definition developed is as follows:

> *A systemic approach is a data-driven, network-wide (or system-level) approach to identifying and treating high-risk roadway features correlated with specific or severe crash types. Systemic approaches seek not only to address locations with prior crash occurrence, but also those locations with similar roadway or environmental crash risk characteristics.*

- **Need to account for data availability** – Systemic approaches require a minimum amount of data (at least crash and roadway/intersection data; see Chapter 2 for more on data issues) to identify factors associated with increased risk across the roadway network. Few agencies had all data on-hand and in the format needed for a systemic analysis, but some agencies were moving toward collecting better data; examples of these are included in the Guidebook. Alternative methods and data sources are needed to make the process accessible to a range of agencies. Considering that many agencies do not have the minimum data, the systemic pedestrian process described seeks to 1) explain the benefits that improving data for a systemic approach can have, 2) offer guidance on essential data needs and how it may be collected or measured, and 3) provide alternatives for using risk factors from prior research to identify safety concerns, and suggest potential alternative data sources to account for exposure when pedestrian or traffic volume data are unavailable.
- **Need to provide robust analysis methods** – The systemic analysis methods used in some tools and by some agencies do not seem to control for user volumes and other potentially important risk factors that may be present to determine the factors associated with increased risk for various crash types. This may result in misattributing risk to factors that are simply correlated with high large exposure or other underlying causes that are either not measured or have not been identified. Although a significant body of research exists with respect to the use of socioeconomic, environmental, and other alternative data sources to estimate pedestrian crash risk, there are few examples of their application in the real world. The Guidebook aims to provide a robust method for risk analysis that controls for vehicle and pedestrian volumes, in step with best practices recommended by the HSM; at the same time, it provides alternatives for risk identification and analysis if data needs for the recommended approach aren't met.
- **Need to provide summary of risk factors** – A limited number of pre-existing tools that include pre-identified risk factors are available (i.e., Pedestrian Intersection Safety Index) that could be useful for initial screening of intersections, but even these have requirements for data that may not be readily available. There is also a growing body of pedestrian safety and injury analysis studies that could be mined to identify reliable risk factors. These could be used to inform others for data types to collect, or be considered for use in risk screening when jurisdictions lack sufficient/detailed crash data on their own network to use for risk analysis.
- **Need to incorporate lower cost countermeasures** – Through the interviews, several agencies indicated low-cost pedestrian improvements have been easier to implement systemically. Despite having formal lists of "approved" countermeasures for their agency, some are reluctant to apply pedestrian countermeasures that may be deemed "more costly" or do not have full support from the public. Cost was one of several criteria used to evaluate countermeasure suitability for application in a systemic process. We did not clearly learn whether agencies widely considered

how well countermeasures were matched to the relevant risks and location types, and whether safety effectiveness was a key consideration.

- **Some jurisdictions started with an effective countermeasure** – Some agencies identified treatments to implement, and then screened their networks to identify potentially suitable locations. This approach is also described in the FHWA Guide (Preston et al. 2013). This approach hinges on selecting treatments with reliable safety benefits, but still may not be fully risk-based, depending on how locations are selected and prioritized for treatment. For example, many locations that lack a certain countermeasure or design may be identified which are not in pedestrian areas, or which are not prone to the type of crash the countermeasure is intended to treat. It is, however, very important to consider the effectiveness of countermeasures that can be implemented systemically, along with the problem type definition, and data needed for accurate assessment of the applicability of that or other treatments, as agencies begin to develop a systemic process. The steps in the process are intertwined and agencies can begin at different points in the process, as long as each step is considered at some point prior to implementation. In a traditional safety management process, the need (or problem type and extent) is usually established before determining the treatment or treatments that are most applicable.

CHAPTER 2: Data for a Systemic Pedestrian Safety Analysis

This chapter provides an overview of the data needed and available for use in a systemic safety analysis process. The findings in this chapter are primarily drawn from the research efforts conducted in Task 1 (literature review and practitioner surveys and interviews, described in Chapter 1).

As described in the Guidebook, the systemic process uses factors with well-established risk relationships—such as roadway, environmental, land use, and behavioral characteristics—to predict pedestrian crash risk in the absence of crash history, or to supplement crash-based analyses. Successful application of a systemic safety process requires identifying common characteristics present at locations where focus crash types occur, establishing key risk factors, and connecting risk factors to potential countermeasures. Various data sources may be required during any given step within a systemic process. For example, traffic volume and pedestrian volume should ideally be considered in identification of risks. If these data are not available for initial risk analysis, other surrogate measures—such as land use, transit, and demographic data—will likely be needed for ranking and prioritizing sites most likely to benefit from systemic treatment. It is unknown how well surrogate measures may serve to represent pedestrian volume or traffic volume, when these data types are missing.

The next sections describe data sources for variables that are likely to be needed at one or more steps of the systemic process. Later sections describe common data limitations and considerations for gathering, estimating, and aggregating data for analysis. These informed the guidance provided in Step 2 of the Guidebook.

2.1 Data for Systemic Pedestrian Safety Process

The following series of tables describe the data sources that may be needed in a systemic process to perform activities such as identifying potential risk factor(s), identifying/screening locations where particular countermeasures may be feasible, and prioritizing treatment plans.

In each table, there is an assessment of the availability of data for use in a systemic process along with other considerations and examples. Data are organized in the following categories:

- Roadway inventory data;
- Motorized traffic data;
- Non-motorized (i.e., pedestrian) traffic data;
- Land use data; and
- Socioeconomic data.

ROADWAY INVENTORY DATA

Table 1 describes characteristics of the roadway and the specific facilities that may be present at a given location. Roadway inventory elements are key variables for a systemic pedestrian analysis and identification of appropriate treatment targets.

Table 1. Roadway inventory data.

Description:	Roadway Inventory Elements
Key variables:	• Speed limit (measured operating speeds are preferred but rarely available, so posted speed is typically used); • Number of lanes; • Roadway width; • Median type/presence; • Roadway classification (may serve as a proxy for Average Annual Daily Traffic volume (AADT); • Intersection type/presence; • Type/presence of stop controls and signals (and operations if available); • Turn lanes; • Presence of bus/transit stop; • Crosswalk marking type/presence; • Presence/type of roadway lighting; and • Presence of non-residential driveways.
Source(s) of data:	State DOTs and local jurisdictions typically collect and maintain roadway infrastructure data; some roadway elements could also be gathered via aerial imagery and/or Google Streetview.
Geographic scale:	Depends on the roadway features included in the inventory; some data may be available only at spot locations, whereas other data (such as posted speed limit or roadway classification) may be available network-wide at the local, regional, or even state level.
Availability:	Varies by jurisdiction and by the roadway feature (e.g., most cities have a complete inventory of where signalized intersections exist but may have sparse data on where marked crosswalks exist); data may also be collected/updated only periodically. Even when inventories of intersections exist, rarely do agencies have an inventory of features of those intersections, such as presence of pedestrian signals, signal timing schemes, etc. State DOTs typically collect and maintain quality roadway infrastructure data for state-owned roads, though some roadway classifications may have more data available than others (highways and urban arterials vs minor/low volume roads) and the data collection schedules can vary widely. Local jurisdictions may have some inventory data for locally-owned roads, but compared to state DOTs, it tends to be less accessible (e.g., in paper rather than digital format), less centralized, and not systematically or routinely collected for all roadways. In contrast, states are required to collect certain roadway elements and tend to have more centralized databases and dedicated staff to manage/update the data. Data, even if maintained as one "roadway inventory," are typically in multiple databases with linking variables. A survey for a 2007 NCHRP synthesis report indicates that timeliness of data varied depending on specific data elements. For example, some states replied on "as built" plans for geometric data. Local road databases ranged from current to more than 20 years old at the time of the survey. Data also depends on the frequency with which older data are archived, so if data are needed for prior years these may be less accessible. In some states, data were maintained and stored by regional districts, in others they were a central office responsibility.

Description:	Roadway Inventory Elements
Considerations:	Data may be in GIS (Geographic Information System) format or other type of linear-referenced database. Different formats and data inventoried at different time periods may be difficult to merge. Ownership of the roadway heavily dictates what data is collected for it. States like North Carolina and Texas, that maintain ownership over a large portion of the roadway network, will have more data regarding roadways in urban areas where pedestrian activity is highest. Operating speed (average or other distributional measures) is a significant risk factor for pedestrian crashes and injury severity that is typically lacking from inventories or other roadway databases.
Example(s):	MMIRE (*Model Minimum Inventory of Roadway Elements* 1.0, FHWA guide) provides a comprehensive description of many variables needed for all types of safety analysis (not focusing only on pedestrian analyses) (Council et al. 2007). The states and cities included in the Highway Safety Information System (HSIS, https://www.hsisinfo.org) may have consistent data, updated yearly. For example, Charlotte, North Carolina has a database of signalized and unsignalized intersections with linked information on operations, turning movements, pedestrian exposure, crash data, and roadway inventory information. Several states, including Ohio, Tennessee, and Illinois, are working to improve their referencing systems regarding local roads to better integrate local roadway inventory data into their statewide inventory databases. Seattle has an extensive data system containing many roadway geometric elements for both segments and intersections. These include a crosswalk inventory and descriptors, signal types, university and school locations, lighting data, building footprints and generalized land use, National Bicycle and Pedestrian Documentation Project (NBPDP) and continuous user count data (limited locations), and crowd-source data (bicycles). In addition, for a recent project, data from multiple other sources were compiled and joined to roadway inventory and crash data. These included transit data, census data, and elevation data. The compiled data were used in a recent pedestrian safety analysis. Similarly, for several recent NCHRP projects (17-26, 17-35, and 17-56), researchers at UNC-HSRC gathered roadway inventory elements at both signalized and unsignalized intersections (from state and local databases and aerial imagery) in several cities, including Philadelphia, Chicago, and Portland.

MOTORIZED TRAFFIC DATA

Table 2 describes variables associated the amount and types of motorized traffic on a segment or passing through intersections. Traffic is a key exposure risk for pedestrian crashes and is needed for a robust systemic safety analysis.

Table 2. Motorized traffic data.

Description:	Motorized Traffic Data
Key variables:	• Traffic volume data such as Average Daily Traffic (ADT) or AADT; • Count of turning vehicles; and • Presence/percentage of heavy vehicles.
Source:	State and/or local jurisdictions typically collect and maintain traffic count data, depending on roadway ownership. AADT data is gathered at spot locations for continuous sections of road, typically using inductor loops or pneumatic tubes across the road. Turning/through movement counts at intersections are typically gathered manually or via cameras/technologies. Typically, the data are true counts (not estimates), though some methods exist to project counts for planning purposes.
Geographic scale:	Counts are typically collected at spot locations by local jurisdictions, but are available system-wide for state-owned roadways, depending on the roadway classification (e.g., arterials).

Description:	Motorized Traffic Data
Availability:	All states routinely collect AADT data for state-owned roadways, with varying degrees of how often and what roadway classes are covered. Sometimes AADT data are an inventory element and are stored in the same database as other geometric data. Local jurisdictions often collect traffic counts at spot locations, which may be driven by requests or as part of a traffic study. Local count data are not typically stored in a centralized location. It is possible that counts for local roads can be extrapolated from nearby state-owned roads.
Considerations:	If actual traffic count data is not available, proxy measures for traffic volume may be drawn from roadway inventory data (e.g., number/density of intersections, number of lanes, etc.). Estimates of AADTs can be generated from modeling if there are sufficient counts at representative locations but count locations typically over-sample high traffic areas (highways and arterials). Model estimates may lack precision for specific locations of interest. There may not be well-established procedures for estimating volumes over segments or for intersections that lack counts and updating them over time.
Example(s):	Schneider et al. (2012) studied factors affecting pedestrian crashes over a 10-year period at 81 intersections with diverse characteristics. They estimated pedestrian crossing volumes over that period from short-term counts at each of the intersections (extrapolating for some intersections from nearby counts). These were incorporated into models to estimate risks associated with pedestrian crashes at the intersections and included a wide variety of other intersection characteristics. Some HSIS states and cities have good count data; in particular, Charlotte has high-quality traffic volume and turning movement count data for a large sample of intersections. Similarly, for several recent NCHRP projects (17-26, 17-35, and 17-56), researchers at UNC-HSRC gathered current and historical AADT data at signalized and unsignalized intersections in several cities, including Philadelphia (traffic count data were provided by the metropolitan planning organization (MPO)), Chicago, Tucson, Phoenix, and Scottsdale.

NON-MOTORIZED TRAFFIC DATA

Table 3 describes non-motorized traffic or amounts of pedestrian activity on a network or at specific locations. Pedestrian exposure is sometimes defined as the amount of pedestrian activity taking place and may reflect the number of occasions, or period of time during which the possibility of a pedestrian crash may arise. Pedestrian exposure can be measured in a variety of ways including counts (of people or crossings at specific locations), number of trips, distance walked, and time spent walking. Counts or estimates of pedestrians walking or crossing at a location are generally used for safety analyses focusing on targeted locations.

Table 3. Non-motorized traffic data.

Description:	Non-motorized Traffic Data (Pedestrian Exposure)
Key variables:	Depending on how the data are collected/formatted and over what period of time, examples include: • Trip count; • Time/distance traveled; • Commute mode share; and • Intersections or segments count data or estimates. Potential proxies for exposure include: • Population and demographic data; • Transit data – see below; and • Land use data – see below.
Sources:	Depending on the scale of analysis and the exposure measure of interest, there are many potential sources for exposure data: • U.S. Census; • National Household Travel Survey (NHTS) or state-level survey; • Federal Traffic Monitoring Analysis System (TMAS); and • Local jurisdiction count data.
Geographic scale:	Can be site-specific (e.g., number of crossings at an intersection) or collected at a city/regional scale or larger and the scale of measurement or potential for aggregation is important for a systemic safety analysis that may also incorporate other risk factors that are measured at different scales.
Availability:	Census and NHTS data sources are widely available. Census data are routinely collected on a rolling annual basis; NHTS data are available only periodically (every 7+ years). Data at a finer scale are typically limited and local jurisdiction count program data collection schedules are highly variable. Some communities have developed on-line databases of local count data (https://sites.google.com/site/bikepeddata/bp-t3-data-clearinghous), including Philadelphia, Pennsylvania; Arlington, Virginia; Portland, Oregon; Eugene, Oregon; Los Angeles, California; and Seattle, Washington. At the state level, only a few have statewide counting programs (Colorado, Washington) but several states such as North Carolina and Minnesota are working on developing programs.
Considerations:	Many other studies have described tradeoffs among various exposure measures, (such as Estimating Pedestrian Accident Exposure (SafeTREC 2010; http://www.path.berkeley.edu/sites/default/files/publications/PRR-2010-32.pdf)) as well as approaches to exposure data collection. NCHRP 797 (http://onlinepubs.trb.org/onlinepubs/nchrp/nchrp_rpt_797.pdf) details several methodologies for determining pedestrian exposure through non-motorized counting, provides practitioners with the fundamentals of how to develop a successful non-motorized counting program, and selecting appropriate counting technologies (Ryus et al. 2014). Data on pedestrian counting and data sharing can also be found in the TRB e-circular: Monitoring Bicyclist and Pedestrian Travel and Behavior Current Research and Practice (http://onlinepubs.trb.org/onlinepubs/circulars/ec183.pdf).

Description:	Non-motorized Traffic Data (Pedestrian Exposure)
Example(s):	SDOT is applying innovative methods to estimate and account for pedestrian exposure in pedestrian crash risk analysis as part of its Vision Zero and systemic pedestrian safety efforts. Short-term manual counts at 50 Seattle intersections from the National Bicycle and Pedestrian Count Program were used in models to estimate pedestrian exposure for all Seattle intersections (Sanders et al. 2017). Along with other roadway and built environment variables, these exposure estimates (both natural log and raw estimates of pedestrian counts) were tested and found to be significant predictors of pedestrian intersection crashes in negative binomial (NB) logistic regression models of crash frequencies (Thomas et al. 2017). The models serve as SPFs and can be used to estimate where future crashes may occur, and to identify some of the risk factors, enabling the city to prioritize locations in need of potential safety treatments.

TRANSIT DATA

Table 4 describes variables capturing elements of transit on the street network or amounts of activity associated with transit. Data on transit service typically pertains to bus facilities and operations (but may include commuter/light rail stops associated with street crossings).

The use of transit data to identify pedestrian safety risks is a more novel approach that may not be used in practice often. The use of transit data may be particularly relevant to systemic pedestrian safety studies, since pedestrian crashes seem to cluster along bus routes and particularly at bus stop locations. This may be due both to numbers exposure and increased activity but also, potentially, to high-risk behaviors, such as when some pedestrians choose to leave the bus and cross in front of the bus where sight distance to oncoming motorists is very limited. There may also be an increase in other traffic-based risks due to increased maneuvers associated with the presence and queuing of buses. Thus, transit data may help to account for pedestrian exposure, as well as other behavioral, operational, and design-related risk factors.

Table 4. Transit data.

Description:	Transit Data
Key variables:	One or more of the following types of transit use data may be available: • Bus route location; • Transit stop location; • Boardings /alightings per stop; and • Transit schedule (frequency of buses, stops).
Source:	Transit data are typically gathered/maintained by the local transit agency.
Geographic scale:	Local/regional
Availability:	Not clear how often transit data is made available for pedestrian safety purposes; no survey respondents or stakeholders interviewed described using this data.
Considerations:	Transit data such as boardings/alightings are likely reflective of pedestrian exposure but may capture other risks as well; more research is needed in this domain.
Example(s):	In Seattle, researchers determined that the total number of buses stopping within a distance of the location of interest was a predictor of certain crash types, even controlling for pedestrian exposure with other variables. In North Carolina, researchers identified a strong association between high boarding/alighting bus stops and routes and pedestrian crash density. Field investigations revealed risk-behaviors associated with some transit locations.

LAND USE DATA

Table 5 describes land use data elements that help to describe the greater context of how lands adjacent to the roadway of interest are used b pedestrians, and what features (such as homes, businesses, schools, parks, etc.) exist that may generate pedestrian or motorized traffic. These variables supplement or may serve as partial surrogates for non-motorized and motorized traffic data if the latter are not available for the entire network.

Table 5. Land use data.

Description:	Land Use Data
Key variables:	• Housing density (in relation to pedestrian crossing); • Employment density (in relation to pedestrian crossing); • Land use type and/or presence of commercial land uses (in relation to crossing); • Presence of mixed uses (in relation to pedestrian crossing); • Presence/density of residential zoning; • Locations of schools/universities (in relation to pedestrian crossing); and • Number of alcohol establishments (in relation to pedestrian crossing).
Source:	U.S. Census Bureau TIGER/Line shapefiles; local/regional sources of GIS data also exist (e.g., county, MPO, and university GIS libraries).
Geographic scale:	Depends on the variable of interest and the data source being used, but most spatial data can be aggregated to a specific site or kept at a spatial/area scale.
Availability:	Widely available.
Considerations:	Requires training to understand GIS-based software applications, data sources, options, formats, and access methods.
Example(s):	Clifton and Kreamer-Fults (2007) established a relationship between pedestrian crashes and commercial access, a higher population percentage of minorities, and mixed land uses near schools. Ukkusuri et al. (2012) found that areas with higher percentages of industrial, commercial, and open land uses have a greater likelihood of pedestrian crashes. Land use data for general transportation planning is common but usage of these data by safety practitioners for traffic/pedestrian risk identification and remediation is not well understood. It may be challenging to identify specific treatable crash contributors at a land-use scale, but such data could be used to screen the network to identify problem areas to further investigate. Field visits could be used to diagnose problems and determine treatments area-wide, which might include a combination of systemic treatments (e.g., consistent signal timing and operations throughout the area) as well as site-specific treatments, based on risk factors and features. In an analysis for SDOT, the research team, led by Toole Design Group scaled land and census measures, such as commercial property density and average income and others, to intersections, and found that both of these measures were associated with increased pedestrian crash risk at intersections (Thomas et al. 2017). Others have performed similar scaling to site-specific locations with similar results.

SOCIOECONOMIC DATA

Table 6 summarizes demographic and socio-economic variables that can help describe characteristics of a population living or working around each network location. Many of these factors can be major determinants of health and traffic injury risk. These elements also supplement traffic volume data and may also serve as partial surrogates if pedestrian and motorized traffic volumes are not available for the risk assessment.

Table 6. Socioeconomic data.

Description:	Socioeconomic Data
Key variables:	• Population (by age and/or sex); • Proportion of transit users and/or commute mode shares; • Vehicle ownership rates; • Employment level; • Income levels; • Education levels; • Household make-up; • Crime indicators; and • Proportion of minority racial groups.
Source:	U.S. Census Bureau (American Community Survey or other household surveys).
Geographic scale:	Data available nationwide. Level of aggregation depends on the variable; may be limited to census tract, block group, or block level; not typically available at the parcel level or finer-grain scales (such as specific roadway crossings).
Availability:	Widely available via Census websites and widely used by researchers; however, its use among transportation practitioners is unknown. Data is collected routinely by the U.S. Census Bureau and made available with little processing lag.
Considerations:	May require some training to understand data sources, options, formats, and access methods.
Example(s):	Green et al. (2011) identified several socioeconomic factors contributing to pedestrian crashes. These include prevalence of single-parenthood, reliance on income-support, and crime. Using census block data, Jermprapai and Srinivasan (2014) found variables with a positive correlation to pedestrian crashes included census blocks with lower than median incomes, a higher percentage of non-English speakers, a higher number of weekly total work trips, a higher number of intersections, and lower education levels. Variables with a negative correlation of pedestrian crashes included median age, population density, and proximity to a major city. Recent Seattle safety analyses identified a relationship between mean income of population residing near the intersections, with lower incomes being more associated with more collisions, even after accounting for pedestrian volume (through estimates), commercial uses, transit, and other exposure-related factors. Again, it may be challenging to use these data in a systemic approach unless the initial problem identification is followed up with an area-wide approach to diagnose and treat similar problems in a systemic fashion. Torbic et al. (2010) and Thomas et al (2017) have both found that measures of average income averaged from census data surrounding an intersection helped to predict pedestrian crash risk, with higher incomes associated with decreasing risk.

PEDESTRIAN CRASH DATA

Table 7 describes pedestrian crash data needed for a systemic safety analysis. Pedestrian crash data are records that describe the incidence of a pedestrian-motor vehicle crash event, and/or the parties involved in a crash, and often some characteristics of crash locations and the time of occurrence. While a systemic process should be able to be applied to locations where crash data are unavailable, crash data still have a key role to play in a network-based systemic analysis using local data to identify safety problems. Specifically, crash data can be used to identify target crash types, and to determine risk-related characteristics of roadways where crashes have occurred in the past. Crash histories may also be considered in prioritization methods, as well as initial analyses to determine crash risks.

Table 7. Pedestrian crash data.

Description:	Pedestrian Crash Data
Key variables:	• Total counts of pedestrian and other crashes per location and time period; • Counts of pedestrian crash types and pedestrian crash severity per location and time period; • Crash environmental factors (light conditions, time of day, weather, etc.); • Characteristics of those involved (drivers and pedestrians' ages, genders, impairments); and • Characteristics of crash locations (may be used in lieu of roadway inventory).
Source:	Typically drawn from police crash reports filed by a local agency and aggregated at the state level. Local jurisdictions may maintain their own crash databases. The National Highway Traffic Safety Administration (NHTSA) provides pedestrian fatality data nationally (through the Fatality Analysis Reporting System (FARS)).
Geographic scale:	Local, regional, state, and national
Availability:	These data are generally available, though some states may do a better job of providing access to the data. There may be a lag, however, in how quickly crash data are made available; 1-2 years is common. More years of data may be more critical than the most up-to-date data.
Considerations:	Many jurisdictions lack detailed data on pedestrian crash types within their crash data, though a system for classifying crash types is available—*Pedestrian and Bicycle Crash Analysis Tool* (PBCAT). Crash type data elements, supplemented by geo-spatial coding, can greatly enhance the ability to link crash types with other features of the environment (such as land use or socio-economic characteristics) to better identify system-wide crash factors and risk patterns by specific locations.
Example(s):	NCDOT has sponsored a multi-year project to develop pedestrian and bicycle crash types and to geo-locate each pedestrian and bicycle crash that is reported statewide. The crash type data are available in a searchable database (http://www.pedbikeinfo.org/pbcat_nc/), so initial systemic analyses can easily be performed to identify systemic crash type and other crash patterns. Crash maps (http://www.arcgis.com/home/item.html?id=b4fcdc266d054a1ca075b60715f88aef) that include crash types and many other crash characteristics are available for exploration and data are available for local agencies to use for safety analyses, project development, and planning uses.

2.2 Complementary Data Sources and Processes

ROADWAY SAFETY AUDIT (RSA)

Table 8 describes potential use of RSAs as an alternative or complement to a systemic process. RSAs can be used within a systemic process to gather necessary data (from observed conflicts and behaviors to roadway and land use features) for a systemic analysis or pattern identification when missing or insufficient data preclude accurate problem determination; and to complete diagnosis to determine appropriateness of planned improvements for systemic safety projects among other potential uses. In smaller jurisdictions or those lacking sufficient crash or inventory data for analysis, area-wide or multi-corridor RSAs could be used to identify common risk patterns for potential treatment on a systemic scale.

A road and/or pedestrian safety audit is a formal, but qualitative safety performance examination of an existing or future road that aims to identify roadway elements that may contribute to crashes and safety problems and to identify appropriate measures to eliminate or mitigate the identified problems (FHWA, Road Safety Audits 2014 webpage). These audits are conducted by a multi-disciplinary expert team that is independent of the project and has relevant expertise in design and operations, and relative safety impacts. The team considers safety from the perspective of all potential road users, along with user capabilities and limitations. Similar—but less formal or unofficial—processes may be called assessments, site visits, or field reviews. RSAs or similar field assessments are widely used after focus areas have been determined through initial screening, public input, or other processes. Dozens of RSAs have been conducted with local agencies, as part of a safety project funded by FHWA, and many states already use RSAs.

Table 8. Roadway safety audit data and processes.

Description:	Roadway Safety Audit/Assessment
Key information:	The data gathered are qualitative assessments but may include observations on: • Built environment and type of land uses the facility serves; • Types of facilities present (sidewalks, crosswalks, median islands, etc.); • Characteristics of people using the areas (for example, older pedestrians); • Origins/destinations; • Where pedestrians cross the street; • Observed conflicts between pedestrians and motorists; • Whether there is sufficient time or sufficient gaps in traffic for pedestrians to cross the street; • Whether facilities along the road are adequate, obstructions are present, etc.; • Nighttime visibility; • Sight distance; • Signal operations; • Speed of traffic; • Driver yielding at crosswalks; • Whether facilities meet Americans with Disabilities Act guidelines; • Compliance with traffic controls and other motorist and pedestrian behaviors; and • Other design and operational factors that directly reflect safety risks and perceptions of adequacy of the facilities to serve pedestrians' needs (and may be unavailable through other data sources).
Usage in systemic process:	• To identify issues (including behavioral issues) and related solutions within an area for which data may be insufficient (even within a broader systemic process); • To review new or planned road improvement projects in a systemic and proactive way, allowing for more consistent review of design and operational factors that may not be detected by ordinary planning and design processes; • To identify common safety issues throughout an area (as examples, an entire neighborhood, or different but similar corridors in a community), that can be treated in a systemic manner (4Es to include education, enforcement, emergency response, and engineering) regardless of whether crashes have yet to occur at all similar locations throughout the area; and • To diagnose and ensure applicability and suitability of systemic treatments to particular locations. The HSM recommends field review and other diagnostic steps before treatments are applied to any location.
Source:	Field data collection
Geographic scale:	Spot locations, corridors, or areas
Availability:	N/A – create the data through the process
Considerations:	Since RSA guides typically recommend reviewing crash reports, the process also allows identification of crash types and patterns from diagrams and narrative information that may not be available or easily analyzed in a crash database. The RSA also allows the investigators to uncover the particular issues present at each location in order to tailor treatments as needed.

Description:	Roadway Safety Audit/Assessment
Example(s):	In 2001, the City of Seattle used the results of the study, "*Safety Effects of Marked vs. Unmarked Crosswalks at Uncontrolled Locations*" by Zegeer et al. (2005) to develop a process to inventory and evaluate approximately 850 uncontrolled marked crosswalks in its jurisdiction. Seattle used the field-based, systemic risk assessment process to identify crosswalks that did not need any changes and crosswalks that could be made safer by adding treatments. The plan divided inventoried crosswalks into three types of interventions based on cost, time of implementation, and complexity of the measures, from simple (e.g., curb ramps) to moderately complex (e.g., bulb outs) to complex (e.g., road diets) (case study in Thomas et al. 2016). A study for Chapel Hill, North Carolina analyzed crash locations, crash type data, and survey data on perceptions of risky areas to identify locations for RSAs (Thomas et al. 2009). Other proactive methods included screening intersections using the PBISI tool, performing traffic speed studies, and using other public input from various town planning processes to identify areas of potential concern. Each of the areas examined during field assessments, including those highlighted by perception data but not by prior crashes, was found to have conditions that affected pedestrian or bicyclist safety. Thus, the accumulation of perception data led to identification of areas with significant safety concerns that would not have been identified by examining prior crashes alone. Field investigations were performed to diagnose problems, and common patterns (such as left-turning motorists not yielding to pedestrians in crosswalks) were treated systemically with regulatory Yield to Pedestrian when turning signs). Over time more comprehensive design solutions, such as median crossing islands and rectangular rapid flash beacons, have been implemented at some problem midblock crossing locations on two major corridors. In Phoenix, Arizona; Chicago, Illinois; and Miami-Dade County, Florida, zonal crash patterns were identified relating to, in these cases, senior pedestrian crashes, in Phoenix and Chicago, young child school-trip crashes, and adult, nighttime mid-block crashes in two neighborhood areas of Miami-Dade. Although the analyses were performed by identifying entire high crash areas, the entire areas were assessed through field investigations (RSAs). High risk factors were identified through the RSAs. Systemic treatments were recommended to treat entire areas or corridors as well as specific locations with the identified risk factors (such as insufficient time to cross at signalized intersections), regardless of where crashes had specifically occurred. See Zegeer et al. (2008) for a report on the Miami-Dade project. Arizona DOT most recently recommended a series of RSAs at prioritized high crash and high-risk locations to complete problem diagnosis and finalize countermeasures selection for potential systemic projects.

PUBLIC INPUT DATA AND PROCESSES

Table 9 describes public input that may supplement other data types and help elucidate safety issues for a more considered systemic safety process. User surveys are another potential method to collect public input on stated demand for where roadway improvements are needed, or perceived risk on where safety risks occur and are an important component of a comprehensive pedestrian safety program. Other methods include development and analysis of complaint databases, Wikimaps, pedestrian/multi-modal plans, and public input through planning processes. Crowd-source data through GIS tracking is another method that can be used to supplement data on where people walk/ride for safety and demand studies. It is important to be aware of potential biases in public input data, and to ensure that all areas in the jurisdiction are well-represented.

Table 9. User surveys and other public input.

<table>
<tr><td>Description:</td><td>User Surveys and Other Public Input</td></tr>
<tr><td>Key variables:</td><td>Locations of problems;
Types of problems; and
Preferred solutions (for different contexts).
Current technologies make it easy for internet and/or mobile device users to identify problem locations and often to describe the types of problems, but may not be representative.
Surveys can also assess needs more generally: where are crossing improvements needed.</td></tr>
<tr><td>Usage in systemic process:</td><td>To identify high-risk locations, more diagnosis is typically needed to identify the potentially relevant countermeasures that might be systemically applied; and
More data may be needed to prioritize locations for improvements.</td></tr>
<tr><td>Source:</td><td>Local jurisdiction surveys and other planning and input processes</td></tr>
<tr><td>Geographic scale:</td><td>May be site-specific or community-wide</td></tr>
<tr><td>Availability:</td><td>N/A – requires data collection, though some data may be regularly collected by communities.</td></tr>
<tr><td>Considerations:</td><td>Multiple efforts may be needed to ensure that data are as representative as possible. For example, crowd source data may be biased toward people who own and carry such devices and not provide representative coverage of all areas. Online surveys may similarly not reach all target audiences in a representative manner. Good outreach may require jurisdictions to go out into communities and be proactive in engaging people who live and walk in all types of areas.</td></tr>
<tr><td>Example(s):</td><td>Eugene, Oregon has a complaint “hotline” phone number for the public to make requests and sometimes uses on-line Wikimaps. Cambridge, Massachusetts uses planning and public requests to prioritize traffic calming through street reconstruction projects on a five-year planning cycle. Resident surveys are the primary methods used to evaluate the effectiveness of traffic calming. Chapel Hill and Carrboro, North Carolina supplemented traditional crash factor and spatial analyses with traveler surveys to identify potentially hazardous crossings. Data were entered into a point database and analyzed to determine the complaint density “hotspots.”
Several Vision Zero Cities, including Washington, DC, New York City, and Boston have developed online Wikimaps to enable the public to enter locations and problems into a map.
Washington, DC map: http://visionzero.ddot.dc.gov/VisionZero/;
Boston map: http://app01.cityofboston.gov/VZSafety/#; and
New York City’s map, closed as of July 2014: http://www.nyc.gov/html/visionzero/pages/dialogue/map.html. The NYC data for over 10,000 concerns were analyzed.
Other examples, also from Vision Zero cities:
Portland, Oregon is using an online survey to ask residents about safety issues and views on potential remedies; and
Seattle acquired STRAVA (https://www.strava.com/) data (GIS-based physical activity and location data collected via mobile app) for bicyclists and these data helped to estimate bicycle counts for the network in light of few counting locations (Sanders et al. 2017).</td></tr>
</table>

2.3 Data Limitations in Practice

From the literature review, survey, and interviews conducted in Task 1, the project team identified a number of gaps related to data collection and use in pedestrian safety analysis and practice. Concerns are grouped into the following categories, described in detail below: 1) gathering data, 2) joining/managing/analyzing data, and 3) calculating risk and exposure.

GATHERING DATA

One inherent concern in the systemic approach to pedestrian safety lies in the lack of detailed corridor or intersection data (e.g., signal timing or phasing, supplemental lighting, etc.), and the identification of high priority sites. As described in the *Systemic Safety Project Selection Tool*, the minimum requirements to successfully identify target crash types and the associated risk factors include network spatial data, crash, facility, crash location, and location characteristic data (Preston et al. 2013). It is further recommended that data pertaining to roadway features, measures of exposure, and intersection features (if applicable) are also collected. Some of the data challenges and potential ways of addressing them are summarized below. This information suggested a strong focus on data needs and compilation for the systemic pedestrian safety Guidebook.

- States and local agencies (e.g., cities, counties, MPOs) may not have available roadway variables found to have a significant effect on pedestrian crashes. For example, jurisdictions may lack of detailed corridor or intersection data (e.g., number and type of lanes, median presence, signal timing or phasing, supplemental lighting, crosswalk inventories, etc.).

  Agencies can augment their databases of the built environment through field data collection and/or virtual approaches; however, these approaches may lead to labor- and resource-intensive efforts.

- Few jurisdictions have count-based (facility level) exposure data available on a network-wide basis.

  While guidance on collecting count data is available, not every agency has begun the process to collect these data at representative locations that can be used to generate estimates for all locations. In addition, such estimates may be subject to a lack of precision for individual locations, as well as potential biases in the samples used for modeling and generating the estimates. The analyses described in Chapter 4 provide an example using pedestrian and traffic volume exposure estimates.

  Non-count-based methods for accounting for pedestrian exposure through surrogate measures are available but use and accuracy of these methods is unknown at present. Additional land use and census variables, along with transit measures, were used in the analyses described in Chapter 4.

- While most agencies can access pedestrian crash data, many crash reports do not have adequate detail about the specific location of the crash nor the events that led up to the crash (i.e., crash type). For example, many pedestrian crash reports do not indicate whether the pedestrian had right-of-way, which leg of the intersection the pedestrian was crossing when struck, or do not indicate the motorist’s actions prior to the crash when a pedestrian is involved (turning, going straight, etc.). Lack of these crash details limits the ability to identify appropriate countermeasures in a systemic fashion since there is a need to account for crash patterns in the analysis.

PBCAT was developed by FHWA to help agencies code crash types to add to their databases, but crash typing also requires time and effort. Examples of agencies that code crash types to aid systemic safety analysis are included in the Guidebook. Options for identifying basic crash types from pre-existing crash variables were also identified in examples included in the Guidebook.

- Not many agencies routinely and widely monitor traffic speed; data may be collected only at spot locations (often of reported concern). Operating speed has a significant relationship to severe and injury crashes of all types, and to pedestrian crash severity. Speed limit may not serve as a good proxy for exposure to higher speed traffic.
- A limited number of pre-existing tools that include pre-identified risk factors are available (i.e., PBISI) that could be useful for initial, systemic screening of intersections, but even these have requirements for data (inventory elements, speed data) that may not be readily available.

JOINING/MANAGING/ANALYZING DATA

- The amalgamation of multiple data types at a system-level often requires input from multiple agencies (potentially both local and state). Even within an agency, compiling data stored in multiple formats or many tables within a database may require significant expertise. For example, the SDOT project experienced some challenges in organizing and joining, vetting, and coding agencies' data as well as data from other sources. However, SDOT staff reported that the relatively small investment required to develop and improve the initial databases was well worth it.

  Agencies can also augment their databases of the built environment through field data collection and/or virtual approaches (Rundle et al. 2011). Examples of using spatial visualization from on-line street view resources were also identified.
- The framework used for manipulating and managing the data is a key consideration, particularly for data with a spatial aspect. For example, roadway inventories with a milepost or linear reference systems may be harder to join with pedestrian crash data or land use data, compared to those using a latitude/longitude (GIS) framework.
- The amalgamation of different data types at a system-level often requires input from and partnership among multiple agencies (potentially both local and state), which may present a challenge for agencies that operate independently. For example, ODOT had inventory data in different formats than the non-state agencies, which limited their study scope to state highways only. Local agencies often compile land use and census variables for planning work, but these data types may not have been widely used by state DOTs.
- Agencies may also prefer to work in GIS formats since much existing data on land use, sociodemographic, and roadway inventories tend to be available in such formats.

The latter three issues above suggest a need for inter-departmental and inter-agency collaboration and organization to develop common data formats and ways of linking the relevant data types.

CALCULATING RISK AND EXPOSURE

Pedestrian exposure can be measured in a variety of ways, including counts (volumes at specific locations), number of trips, distance walked, and time spent walking. While the number of trips, distance walked, and time walked can be gathered from household and intercept surveys, the most common exposure metric for pedestrian safety analysis to date has been pedestrian counts. These or other adequate measures of exposure that can be scaled to specific locations, are essential for a systemic safety analysis.

- For those attempting to analyze pedestrian safety in a systemic manner, the available data seldom incorporate direct measures of pedestrian exposure, which are critical for accurately estimating crash risks.

  In NCHRP 797, Ryus et al. (2014) detailed several methodologies for determining pedestrian exposure through non-motorized counting and provides practitioners with the fundamentals of how to develop a successful non-motorized counting program. It also provides suggestions for selecting the most appropriate counting technique and technologies and the means to improve the accuracies of these methods. Although these counting efforts may require significant funding and planning efforts, they offer safety practitioners an extremely valuable data source to model pedestrian safety. These counts, and/or network-wide estimates developed from representative counts, can be used as a direct measure of exposure in predictive safety modeling and used to assess the risk of particular intersections or facilities in microscopic analysis.

  However, not every agency has the ability or the resources to develop an extensive pedestrian counting program. As a result, practitioners have used readily-available data on features of the built and social environment to predict pedestrian volumes for use in their safety analyses. In general, these data features can be categorized into three classes: socio-economic features (population, income/education levels, proportion of transit mode use, employment levels, etc.), land use and environmental features (housing and/or employment density, land use type, etc.), and traffic and roadway system features (traffic volumes, access to controlled roads, number/density of intersections, transit, etc.) (Pulugurtha and Repaka 2008; Schneider et al. 2009; Miranda-Moreno and Fernandes 2011; and Sanders et al. 2017).

  By aggregating these features at the geographic-area level (e.g., census tracts), rather than for specific corridors, researchers have also developed macroscopic models to predict pedestrian crashes at area scales (Adbul-Aty et al. 2013; Siddiqui and Abdel-Aty 2012; Ukkusuri et al. 2012; Green et al. 2011). However, the area-based analyses are less useful for identifying specific locations in need of improvement within a more traditional systemic safety process. Such results could be used to identify potential systemic focus areas, and/or neighborhood-level needs.

  The forthcoming FHWA *Guide for Scalable Risk Assessment Methods for Pedestrians and Bicyclists (Turner et al. in review)* was identified as a resource to help agencies develop high quality pedestrian volume estimates for use in safety analyses.

- Although a significant body of research exists with respect to the use of socioeconomic, land use, and other data sources to estimate pedestrian crash risk across different spatial scales, there are few, but a growing number of examples of their application relevant for a target location level needed for a systemic approach. In addition to the examples identified in the review above, and developed for 17-73, relevant experiences might include several projects using zonal approaches (as in Miami-Dade County case example of using a Road Safety Audit approach) to pedestrian safety analysis and identification of systemic measures for entire zones or areas with common risk characteristics (Zegeer et al. 2008). Although the area-based analyses did not begin with socioeconomic data—they began with crash data—the area-wide risks identified (such as older-aged pedestrians) were a focus of a zonal "systemic" approach, but required significant use of area-wide RSAs to determined treatable problems.

2.4 Implications for Systemic Processes

As identified in the *Systemic Safety Project Selection Tool*, the minimum requirements to successfully identify target motor vehicle crash types and the associated risk factors include roadway network features (i.e., inventory), spatial data, crash data (location and other crash event /type factors), and traffic characteristic data (Preston et al. 2013). It was further recommended that data pertaining to measures of exposure, and intersection features (if applicable) be collected. This process is feasible given the extensive data available for motor vehicle facilities and operations, but the state of practice assessment suggests that many of the data types have been less available for pedestrian-focused crash analysis.

This section identified sources for the needed data types, examples of uses of these data, and additional data types that may be developed to help to account for pedestrian crash exposure. These include pedestrian counts or volume estimates, and others that are widely available from census data and land use variables. The Guidebook companion to this report is intended to provide guidance on how to improve and compile the data needed to perform more rigorous systemic analyses, as well as offer alternative methods that can be applied with limited datasets. Steps 1 and, especially 2 of the Guidebook, focus most on the data needed for a systemic pedestrian safety process. These steps set the stage for the type of analysis and risk screening process that is possible in the next steps.

CHAPTER 3: Summary of Literature on Risk Factors and Systemic Risk Analysis

This chapter describes the research gathered and reviewed to identify risk factors, and to recommend analysis methods to identify risk factors using local / jurisdictional network data. This research informed the development of content provided in Step 3 of the Guidebook.

3.1 Summary of Pedestrian Risk Factors

RISK FACTORS IDENTIFIED IN INDEPENDENT STUDIES

The literature is abounding with research into potential factors leading to pedestrian crash risk and the relationships between risk and crash severity. Table 10 summarizes pedestrian crash risk factors and the studies verifying their potential to increase pedestrian crash frequency and/or severity. While not exhaustive, this list compiles the most prevalent risk factors identified in the existing literature.

Table 10. Pedestrian crash and injury risk factors identified in existing literature.

Category of Risk Factor	Factors Leading to Increased Pedestrian Crash Risk/Severity	Studies Verifying Potential to Increase Crash Risk/Severity
Roadway Geometric Characteristics	Two-lane roads with a median	Al-Ghamdi 2002
	Increased roadway width (i.e., number of lanes)	Zajac and Ivan 2003
		Zegeer et al. 2005
		Carter et al. 2007
		Harwood et al. 2008
		Quistberg et al. 2015
	Higher order roadway classification	Quistberg et al. 2015
	Intersections with ≥ 4 segments	Dumbaugh and Li 2010
		Quistberg et al. 2015
	Intersections with more right-turn only lanes	Schneider et al. 2010
	Presence of TWLTL	Quistberg et al. 2015
	Lack of stop/yield control	Carter et al. 2007
	Lack of signalization	Carter et al. 2007
	Presence (and number) of bus stops near pedestrian crossing	Harwood et al. 2008
		Ukkusuri et al. 2012
	Lack of a raised median or raised median island for multi-lane roads	Zegeer et al. 2005
		Schneider et al. 2010
	Unmarked Crosswalks (particularly on multi-lane roads)	Zegeer et al. 2005
Motorized Traffic / Operational Characteristics	Increased Speed Limit/Vehicle Speeds	Jensen 1999
		Ballesteros et al. 2003
		Pitt et al. 1990
		Lee and Abdul-Aty 2005
		Lefler and Gabler 2004
		Sze and Wong 2007
		Carter et al. 2007
		Dumbaugh and Li 2010
		Rosen et al. 2011
		Tefft 2013

Category of Risk Factor	Factors Leading to Increased Pedestrian Crash Risk/Severity	Studies Verifying Potential to Increase Crash Risk/Severity
		Kröyer et al. 2014
		Eluru et al. 2008
	Presence of Heavy Vehicles	Atkins et al. 1998
		Ballesteros et al. 2003
		Lee and Abdul-Aty 2005
		Sze and Wong 2007
		Mohamed et al. 2013
		Sarkar et al. 2011
		Strandroth et al. 2011
		Tarko and Azam 2011
		öö et al. 2013
		Zhao et al. 2013
		Haleem et al. 2015
	Increase in overall traffic volumes	Zegeer et al. 2005
		Carter et al. 2007
		Loukaitou-Sideris et al. 2007
		Harwood et al. 2008
		Cottrill and Thakuriah 2010
		Schneider et al. 2010
		Moudon et al. 2011
		Abdel-Aty et al. 2013
		Obeng and Rokonuzzaman 2013
		Haleem et al.2015
Non-motorized (Pedestrian) Traffic Characteristics	Pedestrian Intoxication	Jehle and Cottington 1988
		Zajac and Ivan 2003
		Jang et al. 2013
		Miles-Doan 1996
	Pedestrian age (>~55 - 65 years)	Holubowycz 1995
		Miles-Doan 1996
		Stone and Braughton 2003
		Zajac and Ivan 2003
		Sze and Wong 2007
		Tarko and Azam 2011
		Jang et al. 2013
	Cell phone usage	Nasar and Troyer 2013
		Jang et al. 2013
	Pedestrian volumes	Harwood et al. 2008
		Schneider et al. 2010
		Zegeer et al. 2005
Land Use and Socioeconomic Characteristics[1]	Presence of residential zoning	Pitt et al. 1990
		Moudon et al. 2011
	Increased bus ridership	Quistberg et al. 2015
	Increased employment rates	Abdel-Aty et al. 2013
		Loukaitou-Sideris et al. 2007
		Quistberg et al. 2015

[1] Many of the land use and socioeconomic characteristics may be proxies for pedestrian exposure, as many studies do not control for pedestrian exposure directly.

Category of Risk Factor	Factors Leading to Increased Pedestrian Crash Risk/Severity	Studies Verifying Potential to Increase Crash Risk/Severity
	Presence of commercial office land uses	Clifton and Kreamer-Fults 2006
		Carter et al. 2007
		Loukaitou-Sideris et al. 2007
		Schneider et al. 2010
		Dumbaugh and Li 2010
		Ukkusuri et al. 2012
		Quistberg et al. 2015
	Presence of non-residential driveways within 50 feet	Schneider et al. 2010
	Areas with higher proportions of minorities	Clifton and Kreamer-Fults 2006
		Loukaitou-Sideris et al. 2007
		Chakravarthy et al. 2010
		Cottrill and Thakuriah 2010
		Abdel-Aty et al. 2013
		Siddiqui and Abel-Aty 2012
		Jermprapai and Srinivasan 2014
		Quistberg et al. 2015
	Prevalence of mixed land uses	Mohamed et al. 2013
	Presence of school near pedestrian crossing	Clifton and Kreamer-Fults 2007
		Harwood et al. 2008
		Cottrill and Thakuriah 2010
		Siddiqui and Abel-Aty 2012
	Number of alcohol establishments near pedestrian crossing	Harwood et al. 2008
	Population Density	Abdel-Aty et al. 2013
		Siddiqui and Abel-Aty 2012
		Ukkusuri et al. 2012
		Cottrill and Thakuriah 2010
		Charkravarthy et al. 2010
		Loukaitou-Sideris et al. 2007
	Areas with lower average income	Moudon et al. 2011
		Jermprapai and Srinivasan 2014
	Areas with greater percentage of residents under 18	Schneider et al. 2010
	Areas with lower average education levels	Jermprapai and Srinivasan 2014
Environmental Factors	Night (time of day)	Stone and Broughton 2003
		Klop and Khattak 1999
		Miles-Doan 1996
		Lee and Abdul-Aty 2005
		Sze and Wong 2007
		Eluru et al. 2008
		Jang et al. 2013
	Presence of Fog	Klop and Khattak 1999
	Rainy Weather	Sarkar et al. 2011
		Jang et al. 2013
		Haleem et al. 2015
	Lack of roadway lighting	Mohamed et al. 2013

RISK FACTORS ASSOCIATED WITH CRASH FREQUENCY

To expand upon the risk factors described in the previous section, the team performed additional, in-depth literature reviews to clearly document the types of risks that have been most consistently identified from prior analyses, and identify common ways these variables have been measured and aggregated to databases for frequency-based analysis.

The research team reviewed studies that analyzed factors associated with the frequency of pedestrian collisions, primarily focusing on safety performance functions or multi-level crash and exposure prediction models.

The risks that have been identified to date can only include those that have been measured and studied. Previous studies have primarily focused on intersections (signalized, unsignalized, and all types), with fewer based on segments. Table 11 summarizes variables that were found to be associated with increasing or decreasing pedestrian crashes by the types of locations included in prior analyses. Each "+" or "-" in Table 11 represents one analysis. Some of the data types used in these studies have not traditionally been incorporated into analyses of motor vehicle to motor vehicle collisions or single-vehicle crash types but may be important for a robust systemic pedestrian safety analysis. More details on the studies, crash types, and significant factors are included in Appendix B along with the citations for the reviewed studies.

Key pedestrian crash risks identified from the reviews and analyses for this project include ***traffic*** and ***pedestrian volumes***, ***measures of transit activity***, certain ***land use types*** (in particular, ***commercial*** land uses), census-based measures such as ***average income*** for residents living near facilities, along with various roadway variables that may be candidates for treatment decisions. The risk information was incorporated into the Guidebook, especially in Step 3, determining risk factors. Agencies may consider using and supplementing these risks for the purposes of identifying and prioritizing locations—especially agencies that will not analyze jurisdictional network data to determine risks to use in screening. Agencies that plan to conduct their own analyses may want to compile similar variables for intersection-focused or segment- or corridor-focused analyses along with others that may be important locally.

Table 11. Variables associated with increasing (+) or decreasing (-) pedestrian crash frequency in a specific model. (Some studies performed multiple analyses. See Appendix B for study details and citations.)

Variables / categories associated with Ped Crash Frequencies	Signalized 4-leg	Signalized 3-leg	Unsignalized 4-leg	Unsignalized 3-leg	All Intersections	All segments	Uncontrolled Intersection/ non-intersection
User volumes / activity							
Average daily traffic volume	+ + + + + + +	+ + + + + -	+ +	+ +	+ +	+ + + +	+
Total entering vehicles	+	+	+	+	+		
Total right turn traffic	+						
Total through traffic	+						
Total left turn traffic/left-turning AADT	+			+			
Ratio of left-turning AADT to AADT	+	+					
Ratio of Minor to Major AADT per day	+	+					
Pedestrian volume	+ + + + + +	+ + + + +	+	+	+ + + -	+ + - -	+
Number of daily buses stopping					++	+ +	
Child pedestrian activity					+	+	
Arterial class Major (base category Local)					+ +		
Arterial class Minor (base category Local)					+ +		
Arterial class Collector (base category Local)					+ +		
Proportion of local streets at intersection					- -		
Land Use Characteristics							
Building volume					+ +		
Building volume (commercial)					- -		
Commercial properties	+ + -	+ -			+ + +	+ +	
Institutional area	+	+					
Land use mixed/non-residential					+		
Land use downtown						+	
Land use single-family residential	-	-					
Land use suburban residential						+	
Land use urban					+		

Variables / categories associated with Ped Crash Frequencies	Signalized 4-leg	Signalized 3-leg	Unsignalized 4-leg	Unsignalized 3-leg	All Intersections	All segments	Uncontrolled Intersection/ non-intersection
Urban village categories (increasing development density)						+ +	
Presence of parks	-						
Number of schools nearby	-	-					
Average slope of terrain					-		
Population/Sociodemographic							
Population	+	+			+		
Population under 18					+		
Median income	-						
Mean income					- -	- -	
Older pedestrians							**+**
Number of lanes pedestrians must cross in 1 maneuver	+	+					
Total number of lanes	+	+			+		
Through lanes						+ +	
Number of lanes > 3 (including TWLTL)							+
Presence of right-turn only lanes					+ -	+	
Presence of left-turn lanes	-	-					
Length of crosswalk	+	+					
Mean speed						-	
Speed limit						+	
Intersection controlled by traffic signal					+ +		
Intersection controlled by yield or stop sign					-		
No intersection control					-		
Presence of all red pedestrian phase	- -	-					
Presence of half-red pedestrian phase	- -	-					
Midblock crosswalks						+ +	
Number of intersection legs/approaches	+	-					

Variables / categories associated with Ped Crash Frequencies	Signalized 4-leg	Signalized 3-leg	Unsignalized 4-leg	Unsignalized 3-leg	All Intersections	All segments	Uncontrolled Intersection/ non-intersection
Number of legs: 4-leg compared with 3-leg					+ +		
Number of legs: 5+ compared with 3-leg					+ +		
Number of intersections nearby	+	+					
Number of lanes on largest leg 5+					+ +		
Number of non-residential driveways					+		
Number of transit stops	+ + +	+ +					
One-way traffic flow						-	
Presence of median/median island							-
Presence of parking (striped, on-street)					+	+	
Proportion of crosswalks					-		
Segment length						+	
Presence of two-way enter turn lane						+ +	

RISK FACTORS ASSOCIATED WITH INCREASING CRASH SEVERITY

The research team also reviewed studies that examined factors relating to injury severity when pedestrians are struck by motor vehicles, since a key aim of a systemic safety process is to reduce fatal and severe injuries (see Table 12). These studies primarily rely on analyses of crash data with variables that capture elements specific to each crash. The research team reviewed 15 studies conducted from about 2005 to 2016 that modeled pedestrian injury severity outcomes (given a crash occurred) and that used more up-to-date methods of analysis.

The repetition of findings across numerous studies suggests key variables that are associated with increased risk of more severe injuries when pedestrians are struck. Factors most often and consistently associated with increased pedestrian crash severity are summarized below and incorporated into the Guidebook. This information can be considered at various stages of the systemic process: when identifying target crash types (Step 1 in the Guidebook), developing variables for analysis (Step 2), during risk determination (Step 3); when screening for risk factors (Step 4); or when prioritizing treatments and sites for improvement (Steps 5 and 6 in the Guidebook):

- Older ages of pedestrian, around age 65 and above;
- Larger vehicle types (especially heavy vehicles);
- Darkness, with and without street lighting (although some studies have found lower severity for crashes at locations with street lights, compared to dark and no supplemental lighting);
- Higher speed limits (also driving speed and impact speed);
- Pedestrian crossing the roadway; and
- Pedestrian under the influence of alcohol.

Traffic signals have been associated with decreased crash severity risk, and pedestrian being male has been associated with increased crash severity in a few studies each. More details and citations for the reviewed studies are also shown in Appendix C.

A number of other variables have had more mixed effects in the reviewed studies. This may be due to actual differences in injury severity factors across different jurisdictions, study methods, or other unknown influences.

Table 12. Variables and categories associated with increasing (+) or decreasing (-) pedestrian crash severity.
(See Appendix C for details and citations. Some studies performed multiple analyses.)

Variable	Category (if relevant)	Relationship	No. Studies
Light conditions	Dark, no street light	+ + + + + +	4
	Dark with street light	+ + + +	3
	Dark (not specified)	+	1
Vehicle type	Varied - larger comp. to smaller)	+ + + + + + + + + + + + + +	6
Pedestrian Age	Pedestrian age (~40 - 65)	+ + + +	4
	Pedestrian age (~64 and older)	+ + + + + + + + + + + + +	9
	~ < 10	+ + + + - -	6
Pedestrian action	Pedestrian crossing roadway (with/without signal or at midblock)	+ + + + + + + + + -	5
Pedestrian gender	Male	+ + +	3
Pedestrian alcohol indicators	Pedestrian under influence/alcohol*	+ + + + +	5
Traffic Control type	Traffic control = Type other than signal (stop sign)	+ + +	3
Speed limit	Increasing	+ + + +	4
Speed limit	25 - 50 comp. to < 25	+ +	2
	> 50 (compared to < 25)	+ +	2
Vehicle speed		+ +	2
Impact speed		+ + +	3
**Note that two studies also indicated driver under influence increased severity risk in pedestrian crashes*			

Some of the above types of factors may be difficult to account for in a systemic analysis. There are various potential methods for capturing some of the risks associated with crash severity when jurisdictions analyze crash risks by location for a systemic approach. For example, proportion of heavy vehicles may be captured as a traffic characteristic in addition to general traffic volume. Some of the other risk factors associated with severity can be considered during the identification of focus crash types for analysis such as nighttime crashes, crashes involving older pedestrians or alcohol, or pedestrian crash type involved a pedestrian crossing the roadway. Such factors may be difficult to account for in analyses of crash frequency, unless there are sufficient crashes of different types to perform separate analyses.

3.2 Risk Analysis Method Rationale and Considerations

In a systemic process, risks that increase the likelihood of that target crash occurring should be determined. How best to estimate the risk of future pedestrian crashes or to allocate resources to treat a network systemically is not well-known at present. Analysts and agencies used various model forms to estimate factors associated with crash frequencies (several were highlighted in Chapter 1.) However, the team was charged with identifying a robust and reliable methodology for determining crash risks.

The research team reviewed published research syntheses of analysis methodologies, and agency guidebooks developed to support implementation of the first HSM and systemic safety processes. In reviews of published examples and follow-up with agencies for development of case examples, other needs and challenges for a systemic pedestrian safety process were also identified and taken into consideration in identifying the recommended systemic analysis approach. Although a wide variety of analysis methodologies are available with varying strengths and limitations, none of the methods discussed in syntheses seems to offer substantial enough improvement, without also contributing substantial new challenges, to the existing HSM crash prediction methodology. This situation could, however, change at any moment. (See Lord and Mannering 2010; Mannering and Bhat 2014 for in-depth reviews of crash frequency analysis methodologies. See Savolainen et al. 2011; Eluru et al. 2008; and other studies listed in Appendix C for more information on analyzing crash severities.)

The Guidebook recommends following the basic HSM practice (i.e., developing SPFs), but specifying more crash factors in a model-based approach to identify risk factors relevant to a specific location type within a jurisdiction. As an alternative, agencies could identify risk factors from prior research or alternate type of analysis to use in initial location identification, and develop base model SPFs (traffic and pedestrian volumes only) to assist with prioritization. Both of these alternatives require traffic and pedestrian volume data for the target network locations of interest (e.g. intersections or segments).

The primary advantages of developing crash prediction models or SPFs in a systemic pedestrian safety analysis (as well as a crash-based approach to safety) are the following:

1. Local crashes are used to identify crash-related risk factors relevant for the network.
2. The modeling process can examine a number of potential risk factors, while simultaneously accounting for traffic and pedestrian volumes or activity-related exposure surrogates, and other risk factors.
3. The significant roadway factors identified in the model can be used to screen sites for potentially treatable risk factors.
4. The method generates more reliable estimates of overall crash potential compared to crash frequencies, an optimal outcome for a systemic approach that aims to prioritize based on risk. The method accounts for regression-to the mean phenomenon that affects crash frequencies by examining risks across many locations using multiple years of data. Sites with risk-related characteristics may be further prioritized, as needed, using the more reliable crash prediction estimates generated by model outputs. The metrics generated can also be used in economic analysis and to help justify treatment of these locations.
5. If agencies develop pedestrian crash-based SPFs, the models may also be useful for identifying *high* or excess expected *crash sites*.

This approach should be familiar to agencies that follow HSM practice to reliably estimate potential high crash locations. Compared to risk identification methods based on crash frequencies, the more fully-specified SPF-development method is beneficial because, as mentioned, it accounts for the randomness of crash events and the over-dispersion of low-crash frequencies across sites (Gross et al. 2016a). A robust, crash prediction model can also help illuminate significant factors and therefore identify these common elements of risk (Mannering and Bhat 2014).

NB regression is, at the present time, a widely accepted and popular method to analyze crash frequency data because it accounts for the regression-to-the-mean phenomenon and other important characteristics of crash data (HSM 2010; Srinivasan and Bauer 2013). NB regression uses a Poisson-Gamma distribution to account for randomness and can utilize a range of data transformations to cope with extreme values and identify the form of the relationship (Mannering and Bhat 2014). Variables in the dataset can be entered and tested in the model for significance to find which elements increase the likelihood or risk of a crash and which decrease that risk.

In addition, recent reports on the systemic process and examinations of the reliability of different safety ranking metrics highlight the need for reliable safety performance metrics that can be used to rank sites, even within a systemic risk assessment process (Gross et al. 2016a, b). No data are perfect, and methods that rely only on risk assessment, without consideration for where prior crashes have actually occurred across the network, may be missing important data elements and factors that should be considered in prioritization. SPFs can generate more reliable ranking measures for both crash-based and systemic approaches to treatment, and for both approaches, metrics that do not require the analysts or practitioners to develop subjective ranking methods (Gross et al. 2016b).

Not all risk factors may be uncovered by NB regression modeling. Important factors may not be selected if other highly correlated variables are included in the model. Other analysis methods have also been used to determine risk factors, and such methods may continue to evolve. For example, Saleem et al. (In Review) describe their use of Random Forest analysis to determine and rank factors by importance in terms of their association with crash frequencies. The analysts further describe the use of Random Forest plots of predicted crash frequencies as functions of the predictive variables to determine the direction of effect of each separate variable. Thus, the outputs give both importance and direction of effect for each variable independently. The purpose of this research was to identify risk factors, and there was no discussion of metrics for ranking locations based on overall risk.

In summary, progress has been made in understanding risks for frequency and severity of pedestrian collisions by locations relevant for systemic treatment identification, and it is likely that further progress will be made as data and analysis methods continue to improve. Whatever analysis methods are used, analysts and practitioners will continue to need to apply logic and a keen understanding of risk concepts when identifying data for analysis, analyzing data and interpreting results, and applying the results to screen a network for risks.

Besides the use of identifying specific risk factors, developing SPFs seems to provide an additional important benefit in a systemic risk analysis, in that the overall estimates of crash potential by site (including SPF-predicted or crash-weighted Empirical Bayes (EB) estimates) provide useful insight for prioritizing locations for treatment.

Agencies have been able to successfully use prior knowledge from research and expert input to select roadway-related risk factors to use in network screening. However, agencies applying these methods, lacking crash estimates, have also needed to acquire additional data types to help determine which locations, including sites with no or low prior crashes, should be priorities for treatment. Prioritization may then require subjective weighting processes, and additional work-arounds for economic analysis. The data needs and work load seem similar but are performed in a different manner or order. Case Example 3 in the Guidebook provides an example from Arizona DOT of the approach of using prior risk information, supplemented with additional data gathering and work-arounds for economic analysis.

The next chapter describes the use and results of applying the recommended analysis approach—the development of SPFs using network-wide data from a single jurisdiction.

CHAPTER 4: Research to Develop New Risk Factors

This chapter summarizes the data and results of analyses of two types of pedestrian collisions that occur at midblock or segment locations. As defined in this Report, a systemic safety analysis involves identifying target crash types, and identifying and screening for risks associated with frequency of collisions of that type. It further involves identifying many locations that may have those characteristics for potential treatment, even if prior crashes have not occurred. Pedestrian-motor vehicle crash risks may be different from those that are associated with motor vehicle only collisions, and the crash types may not be as well specified. A growing, but still limited number of studies have analyzed the effects of traffic volume, roadway characteristics, and other built environment and population characteristics on pedestrian collision occurrence at intersections. Very few studies have, however, analyzed risks associated with the frequency of midblock pedestrian collisions. Midblock pedestrian collisions tend to be more severe in nature, and also more dispersed and are therefore a potential focus of a systemic approach.

This analysis aimed to add to the knowledge base about risks associated with midblock pedestrian collisions, but it also serves as a case example of a potential systemic pedestrian safety analysis using local, network-wide data. This chapter describes the data, how data limitations such as identifying 'crash types' and accounting for exposure were addressed, and how the results were applied in the systemic process.

Model outputs, including SPF-predicted or EB estimated crashes can aid in ranking locations for potential treatment— locations that both have, and have not, experienced prior crashes. This is an inherent 'risk-based' approach to identifying and prioritizing sites for potential treatment. Project team members analyzed data from Seattle, Washington to identify factors associated with two types of pedestrian-motor vehicle collisions at segment (midblock) locations: 1) pedestrian struck by a through motor vehicle at a segment location, and 2) all types of pedestrian-motor vehicle collisions that occurred at night along a roadway segment. The analyses identified variables and risks associated with these collision types that other agencies may wish to collect or compile for their own analyses, or in lieu of that, consider for risk-based screening.

4.1 Background

Crashes at midblock and uncontrolled intersection crossings typically account for high frequencies of pedestrian crashes (in some jurisdictions, a majority) and are also often, on average, more severe in outcome with proportionally more fatal or severe injuries compared with pedestrian crashes at traffic-controlled intersections. Based on these criteria, pedestrian crashes at uncontrolled, midblock locations would certainly be considered a focus pedestrian crash type in many jurisdictions. However, segment collisions tend to be widely dispersed across the network, even more so than intersection collisions. This situation is a potential reason to take a systemic approach to treatment, but at the same time, may increase challenges for identifying risks. It is necessary to use more than just "high frequency sites" to identify risk patterns, since high frequency crash locations may be virtually non-existent, and if there are high frequency crash locations, regression to the mean issues may lead to misleading indications of priority sites.

This project had a rare opportunity to analyze a database from the City of Seattle containing counts of pedestrian crashes for all non-freeway street segments to help identify risks associated with pedestrian crashes. The presence of darkness compounds the risks associated with pedestrians crossing or being in the road at unexpected locations such as midblock. Thus, our analysis focused on two key types of pedestrian crashes at midblock locations: 1) pedestrians crossing the road-struck by a through motor vehicle along a segment (non-intersection location) at any time of day and 2) all pedestrian-motor vehicle collisions that occurred at night along such segments.

PRIOR RESEARCH

This modeling approach was demonstrated in the first edition of the HSM and has been primarily used to develop SPFs and metrics to screen and rank locations according to various crash predictions or estimates, especially to identify high expected or excess expected crash sites. However, by developing more fully-specified models (that is with more variables potentially associated with crashes), this approach can also be used to identify crash prediction factors, which, if carefully done, can be interpreted as factors associated with crash risk. The significant variables in the final models provide an indication of risks for pedestrian crashes and, as mentioned, the crash prediction estimates from the models are useful for systemic project prioritization.

The first edition of the HSM incorporated SPFs developed for pedestrian crashes at 3- and 4-leg signalized intersections. Traffic volume (both total entering AADT and the ratio of minor to major road AADT) and pedestrian volume were both positively associated with pedestrian crashes. Earlier, Lyon and Persaud (2002) analyzed the functional relationship of pedestrian crashes to traffic and pedestrian volumes. In Lyon and Persaud's study, total entering AADT, pedestrian volume (8-hour count for all approaches), and the proportion of left turning AADT to AADT were significant positive predictors of pedestrian-motor vehicle collisions at urban, signalized intersections. In each model tested, pedestrian volumes substantially improved model crash predictions, but in each case, the exponent was less than 1, indicating that the relationship of crashes to pedestrian volumes is non-linear (Lyon and Persaud 2002). If these, or other important factors associated with collisions are not measured or accounted for in the models, there is a chance that confounding with these missing measures may obscure the true risk relationships (Mannering and Bhat 2014).

Several additional studies since the HSM have attempted to identify risks associated with pedestrian collisions at intersections. Beyond the base models (traffic volumes only) included in the HSM, the researchers who developed the SPFs identified the maximum number of lanes crossed by a pedestrian in any one crossing maneuver (exclusive of medians/median islands), presence of bus stops, and number of commercial structures as positively correlated with crashes, while average per capita neighborhood income was negatively correlated with crashes (Torbic et al. 2010).

Motor vehicle and pedestrian volumes were positively, but non-linearly, associated with pedestrian crash risk in each of the reviewed studies cited below as well. The following variables were also found to have an association with increased crash risk at intersections: the presence of right-turn-only lanes (Schneider et al. 2010); commercial driveways near the intersection (Schneider et al.; Strauss et al. 2014); increasing commercial property density near the intersection (Schneider et al.; Miranda-Moreno et al. 2011; Thomas et al. 2017); increasing transit activity (Thomas et al.; Miranda-Moreno et al.); and youth population proportion (under age 18) (Schneider et al.). Negative correlations with crashes have been associated with the presence of medians (Schneider et al.; Zegeer et al. 2005), protected pedestrian signal phasing at signalized intersections (Strauss et al.), and, again, mean income of area population (Thomas et al.). These and other risks are included in Chapter 3.

There have been fewer studies examining risks for pedestrian collisions at segments. Zegeer et al. studied *Safety Effects of Marked Versus Unmarked Crosswalks and Uncontrolled Locations* that included both intersection and uncontrolled midblock crossing locations with no signals or stop signs (Zegeer et al. 2005; Zegeer et al. 2002). This study was intended primarily to assess the safety effects of marking crosswalks at uncontrolled crossing locations, but also to identify factors that might affect risk at the two types of locations (marked and unmarked). The researchers collected data on traffic and roadway variables at 1,000 marked crosswalks at uncontrolled locations and 1,000 comparable locations without marked crosswalks from 30 cities across the U.S. A majority of the sample location were at intersection-related crossings of main roads with no traffic control, with a smaller number at midblock locations. The researchers developed separate safety performance models for marked locations and unmarked locations controlling for traffic and pedestrian volumes. The factors associated with greater risk at marked, but uncontrolled, crosswalk locations included increasing pedestrian crossing volumes, higher volumes of traffic, more than two lanes, and presence of a raised median (which reduced risk). They did not detect an effect of higher speed limits, controlling for these other factors, but noted that there was not much variability in speed limits in the data (with 93 percent of sites having limits between 25 to 35 mph). Risks associated with unmarked locations also included higher volumes of pedestrians and higher ADT, and raised medians, which again reduced risk. Results were also found to be highly consistent across eight different major cities that were part of the sample (Zegeer et al. 2002). Painted medians and center TWLTLs were not associated with similar safety effects (with early models suggesting a negative effect for TWLTLs (Zegeer et al. 2002)). As mentioned, a majority of the marked crosswalk sites were at uncontrolled intersection approaches.

For segments in general, there have been few studies that count crashes that might occur at any location along a segment and analyzed risks besides traffic volume. One challenge with such studies is counting or estimating the number of pedestrians that may cross anywhere along a segment to account for this type of exposure. Another issue may be matching crashes to the location where they occurred. Gates et al. developed SPFs for crash prediction and use in screening based solely on traffic flows (pedestrian volumes were unavailable) for pedestrian crashes for eight types of urban segments disaggregated by number of lanes, one-way/two-way flow, and whether the road was divided/undivided in accordance with Michigan urban trunkline road facility types (Gates et al. 2016). Vehicular flows were positively correlated with pedestrian crashes in most, but not all, of the disaggregate models. Since the data were disaggregated for analysis by many roadway-related pedestrian risk factors, these could not be identified as crash risks through the modeling process. Built environment or activity measures do not seem to have been examined or used to help control for pedestrian activity-based exposure. Similarly, Abdel-Aty et al. (2016) developed SPFs for Florida for different road segment (and many other) facility types, also based solely on traffic volume (AADT) measures, and disaggregated by different features potentially associated with pedestrian crash risk.

Case control methods were used in at least one study to analyze pedestrian crash risk using logistic regression analysis, which assesses the likelihood of a crash occurring where a feature or features was/was not present. Segments and intersections with child pedestrian crashes were used as cases, which were matched to segments and intersections without crashes on the basis of geography, socio-economic indicators and crash year (Bennet and Yiannakoulias 2015). In this study, crashes were assumed to occur at a segment midpoint, and the location characteristics were assumed for the midpoint as well. Except for estimates of traffic volume and pedestrian activity, all measures were dichotomous (present or not present at the segment or intersection), and included presence of bike lanes, bus stops, on-street parking, land use type, speed limit (> or </= 50 km/hr), fire hydrant, sidewalks, one-way, and yes/no within 150 meters of a school. The researchers tested several estimates of child activity to account for exposure in the models: a shortest route (to school) method, a preferred route (to school) method, population density, and model results in terms of other significant factors. Their signs and magnitudes were very stable, regardless of which estimates were used. This finding suggested to researchers that child population (from small area estimates) assigned to locations might serve as an adequate surrogate for child activity, reducing the burden for analysts and others to develop detailed exposure/activity estimates. For intersections, traffic volume, and pedestrian activity were positively associated with child

pedestrian crashes along with mixed land uses (residential and non-residential) compared with residential. Factors that were negatively associated with child pedestrian collisions occurring at an intersection included yield or stop sign, or no traffic control, compared with signal control. For segments, estimates of child pedestrian activity and segment length were significantly and positively associated with crashes at segments, but the researchers could not identify other micro-level measures of midblock conditions that were associated with pedestrian crashes (Bennet and Yiannakoulias 2015). These findings may be partially related to the limitations of the study and data precision as well as the absence of some measures (number of lanes, street width, median presence) that might be associated with pedestrian crash risk.

The present analyses aimed to help fill gaps in understanding of pedestrian crash risks at segment locations by analyzing a dataset containing a large set of potential explanatory variables. The results may help agencies better understand potential risks for such locations in their own jurisdictions to help prioritize where systemic improvements may be warranted. The information can also help identify important data types agencies may need to collect for analysis and screening within their own jurisdictions. The analyses also serve as one example of a method to identify crash-related factors for potential systemic treatment that also provides other benefits in the prioritization process by generating crash prediction estimates. These metrics are useful in a systemic approach—especially since many locations may have no prior crashes, but based on these crash estimation metrics, may be likely to have crashes in time. Any pedestrian safety approach, including hotspot/high crash approaches, that seeks to identify the most cost-effective locations for improvement may benefit by developing these models and metrics.

4.2 Research Methods

A systemic approach aims to identify and treat risks across the network. However, the best method to date for identifying such risks is to analyze factors associated with where prior crashes have occurred across the network. Thus, in the present study, accepted analytic methods, specifically NB regression model building, were used for analyzing crash frequency by location to identify factors associated with prior crashes. Many roadway, built environment, and volume and activity/exposure metrics were included as potential crash predictors.

To help address the desire to consider more severe injury risk, while making use of all-severity of crashes in the analysis, this study focused on two segment-related pedestrian crash types that were associated with a higher than average percentage of more severe injuries (fatal or serious injury type).

DATA USED

Data for the entire Seattle city street network were included. Seattle is a city of approximately 704,000 residents covering 83.9 square miles, for an average population density of 7,251 persons per square mile (Bureau, United States Census 2010).

Segments Data

A wide variety of roadway, land use, and demographic data were also compiled and linked to each segment. In the Seattle data, a large array of roadway variables was linkable to each segment via a unique segment identifier. Land use and demographic variables from U.S. Census data were also linked to each segment using spatial buffering methods.

Land use and other measures of the built environment and populations around each segment that have been found to be associated with activity (potential exposure surrogates) and/or crashes in prior studies were also developed and tested in the models. Besides typical roadway descriptors, measures of light pole distributions, and average slope of surrounding terrain or maximum slope of the segment were also derived from available data. Transit data were also derived from a consolidated regional transit database. Variables available for analysis and their sources are shown in Table 13.

Table 13. Summary of variables available for analysis and the source.

Source	Variables
City of Seattle – DOT (SDOT)	
Crash and Roadway relational databases; pre-defined linkages based on segment key (midpoint of block used to aggregate lanes/linear data)	Numbers of through lanes; median presence, TWLTL presence, speed limits, arterial and transit classifications, striped parking, other specialized lanes (bus-only, bus/bike), one-way/two-way traffic flow, width of the roadway, segment length traffic control and turn lane presence at adjacent intersections, sidewalks, bike facilities, midblock crosswalks
Generalized land use data and development density designations (geo-spatial) (City of Seattle, parcel database)	Commercial property density, university locations, school locations, urban village development types, other land use variables used in estimating pedestrian/bike volumes
Light pole data (geo-spatial)	Light pole count per segment, light poles per 100 feet by segment
Traffic volume estimates were developed for SDOT by a consultant	Traffic volume estimates (two different estimating procedures generated two sets of ADT estimates: Pred_ada; Pred_rfr)
Pedestrian volume estimates were derived from an earlier project for SDOT	Average annualized daily pedestrian volume estimate (AADP)
Bicycle volume estimates were derived from an earlier project for SDOT	Average annualized daily bicycle volume estimate (AADB)
Other Sources	
Census block level demographic/employment data (U.S. Census)	Population, employed population, mean income, and older and younger population percentages
Google Transit Feed Specification, Sound Transit (dataset includes King County metro and any other transit providers in the region)	Transit stop location and schedule data – combined to develop estimates of average weekday buses stopping within range of segment midpoint
National Elevation Dataset (U.S. Geological Survey/USGS)	Maximum percent slope on segment, average slope of terrain surrounding segment midpoint

The land use and demographic variables were aggregated based on proximity to the midpoint of each block segment. Population-based factors were averaged for census blocks within a given radius of the segment midpoint or in a few cases, the average between adjacent intersections for the segment.

Although operating speeds are associated with fatal and injury crash frequencies (HSM 2010, Vol I, p. 3-57) and impact speed is associated with pedestrian injury severity (Rosén and Sander 2009; Rosén et al., 2011; Kröyer et al. 2014), operating speed data was not available for analysis. Impact speed is not feasible as a screening risk measure. Instead, speed limit was used as a surrogate measure for operating speed. Although this measure is problematic due to the lack of information on how well speed limits represent actual operating speeds, at the time, these were the most complete speed data available. In the Seattle data, there was also a general distribution of speed limits of 35 mph or lower on a majority of segments, and a strong association between functional classification and speed limit. However, leaving speed out of the predictive models risked losing one dimension of pedestrian crash risk. Higher speed limits were also combined into two categories because of low numbers of segments with the higher limits.

Exposure Estimates

Ideally, measures of pedestrians crossing volume within a block would be used, but such counts or estimates were not available, and would be very difficult to gather for the entire length of segments. In this study, several different exposure methods were used to help account for pedestrian activity around the roadway network that may contribute to crash risk. In addition to the pedestrian and motor vehicle volume estimates, estimates of bicycle volumes, presence of nearby bus stops, and average frequency of daily buses stopping near the block midpoint were derived.

As described in more detail in Sanders et al. (2017), ballpark estimates for pedestrian volume at intersections were developed by modeling count data from 50 intersections in the City of Seattle. Estimates were annualized using factors derived from an earlier study from the City of San Francisco (Schneider et al. 2012), a city deemed to be similar to Seattle in regard to pedestrian infrastructure and activity. The final model estimate yielded a Pseudo R2 of 0.759, which was comparable to correlations in other such exposure estimation models. Significant variables included the number of households within 0.25 mi, land use (the number of commercial properties within 0.25 mi, and the presence of a university within 0.25 mi). The mean value for the ratio between the annualized counts and the estimated counts was 1.39, with an overall standard deviation of 0.97, suggesting a reasonable fit with the data (Sanders et al.). These intersection-based estimates were then split and averaged into segments between adjacent intersections (AADP_MB) for use in the present analyses. These values warrant additional validation but were thought to be preferable to including no pedestrian volume estimates. In addition, other land use and demographic measures that were not included in the volume estimation model, were tested and included in the SPF development process to help account for pedestrian activity.

Similar to pedestrian volume estimates, bicycle estimates (AADB_MB) were developed using City of Seattle counts as discussed in (Sanders et al. 2017). A variety of predictive variables were tested in regression models to predict data from 46 screenline counts and annualized using factors provided by the city. These estimates and log-transformed values were also tested in the models.

Collisions between motor vehicles and pedestrians are understandably products of the exposure of pedestrians to motor vehicle traffic and other transportation modes as already discussed. Thus, it is necessary to account for traffic volume data in crash prediction modeling. Due to limited traffic volume data that were originally available, predictive models were also required to develop estimates of AADT for all segments. A consultant had previously developed estimates using two different machine learning algorithms to predict AADT from existing counts, based on roadway descriptors such as arterial classification, number of lanes, roadway width, segment length, one-way, dead-end status, population and employment, among a number of other variables (SDOT Memorandum, unpublished). The first, a random forest regression model, used a learning algorithm to build trees to identify associations between variables in order to unify multiple models into a single prediction. The variable for this estimate was coded pred_rdf, and it was found to provide strong predictive accuracy for traffic volumes on segments. The second estimation method, ADA-boosted regression, uses a meta-algorithm to create a large range of estimators. It is similar in function to a random forest but better handles incorrect classifications in observations. The output of this algorithm is the pred_ada variable. By some metrics, the ADA-boosted prediction was even more accurate; therefore, the project team tested both predictions in the current crash models.

Crash Counts

This analysis used eight years of reported crashes (2007-2014) to develop the pedestrian crash models discussed in this paper. As mentioned, researchers counted two different motor vehicle/pedestrian collision types and assigned the frequencies to each segment. Seattle had previously assigned collisions to either an intersection or a segment location using the same unique segment identifier that was used to link roadway variables. The two crash types were defined using segment location indicators, and 1) a "motorist maneuver" variable available in the data and 2) a variable denoting light conditions at the time of the crash.

The project team developed separate models for each crash type but used the same set of available predictor variables. The two "crash types" included:

- Crashes involving vehicles driving straight colliding with pedestrians at segments (non-intersection locations) (PMV_Strt); and
- All types of motor vehicle-collisions that occurred under various dark conditions along segments (PedDark).

In the data set, there were 802 PMV_Strt collisions over the eight-year study period and 404 PedDark collisions that could be matched to segments. These two crash types overlap as shown in Table 14, and both are subsets of all pedestrian crashes at segments. Approximately 39 percent of the set of PMV_Strt crashes also involved dark conditions. A majority (78 percent) of crashes at night also involved motorists traveling straight, with smaller numbers involving turning vehicles, backing vehicles, and other miscellaneous types (Table 14).

Table 14. Overlap of the two analyzed collision types.

Light Conditions	PMV_Strt	Left turn	Right turn	Backing	Other misc	Total PedDark
Daylight	443					
Dawn	21					
Dusk	10					
Dark - Street Lights On	294	34	14	0	20	362
Dark - Street Lights Off	7	1	0	0	0	8
Dark - No Street Lights	13	1	1	19	0	34
Other/Unknown	14					
Total PMV_Strt	802					404

Within these types, all severity levels (as reported in the crash data) were used in the analysis; however, as mentioned above, each of these types had a higher average percentage of fatal or serious injury outcomes (18 – 18.5 percent) compared with pedestrian crashes of all types and at all locations (12 percent – data not shown).

Analysis Variable Distributions

Table 15 shows the distribution of the scalar variables that were tested in the SPF development analyses. Data on the focus crash types is also presented. Although there was a range of 0 to 8 pedestrians struck by through motor vehicle (PMV_strt) collisions, the 802 collisions were widely dispersed, illustrating the challenge of identifying patterns and targeting treatments based on limited 'high crash' areas. Only eight segments out of more than 23,000 segments in the database had 4 or more pedestrian collisions within the eight-year study period; 26 in total had 3 or more. Zero crashes were observed for a majority of road segments, with 577 segments having 1 crash over eight years. Similarly, the 403 PedDark collisions occurred across 356 segments.

Only 219 segments had one or more midblock crosswalks (shown as a scale variable in the table below). Lane type and number variables were those present at the segment midpoint, acknowledging that roadway profiles sometimes change over the length of a segment. The research team deemed that the mid-point location was a valid way to capture the average profile for the segment.

Table 15. Descriptive statistics of scalar variables tested in models.

Variable Name	Description	No. of segments	Minimum	Maximum	Mean
PMV_Strt	Crashes between vehicles traveling straight and pedestrians crossing at street segments	23,636	0	8	0.03
PedDark	All crash types between vehicles and pedestrians at street segments at night	23,636	0	4	0.02
Pred_ada	AADT estimates from ADA-boosted regression	23,404	3.0	93,600	4,330.7
Pred_rfr	AADT estimates from RFR prediction	23,404	865.8	78,535	4,181.1
AADP_MB	Estimate of pedestrian volumes along the segment	23,636	0	9,213	732.4
AADB_MB	Estimate of bicycle volumes along the segment	23,636	35.0	11,216.6	165.2
Transit_stops_150_ft	Average number daily buses stopping within 150 ft adjacent to intersection [1]	23,612	0	1,567	35.3
LightPoles	Count of light poles on segment	23,570	0	71	2.8
LtPole100ft	Light poles per 100 ft on segment (GIS-based)	23,558	0	5.6	0.68
Tenth_comm	Commercial properties within 0.10 mi of segment midpoint	23,620	0	64	6.2
Tenth_pop	Population with a 0.10 mile	23,620	0	5042.5	701.3
Quart_emp	Employment 0.25 mi	23,620	0	98,536.00	2,512.31
Tenth_bus	Number of bus stops within 0.10 mi	23,620	0	18.5	1.5
Mean_inc	Mean income of area residents ($)	23,584	3,393	225,813	80,096.6
MB_xwalks	Midblock crosswalks	23,636	0	4	0.01
SEGLENGTH [2]	Length of the segment (ft)	23,622	16	9,302.60	406.7

Variable Name	Description	No. of segments	Minimum	Maximum	Mean
SURFACEWIDTH	Width of surface of the roadway segment (ft)	23,620	0	295.0	24.6
Avg_slope_pct_half_mi	Average slope percent over 0.5 mi surrounding segment midpoint	23,612	0	6.3	2.0
Pct_age65plus	Percentage of population 65+ years	23,620	0	0.61	0.12
Pct_kids	Percentage of population (< 18 years)	23,618	0	38.0	16.4
Univ_dist	Network distance to nearest university (mi)	23,590	0	7.6	1.8
[1] Many of the scalar measures (unless noted) were maximum or average values from the adjacent intersections.					
[2] The values for segment length were derived from GIS linear reference data rather than actual measurement.					

Table 16 shows the distribution of categorical variables tested in the NB models.

Table 16. Descriptive statistics of categorical variables tested in models.

Variable Name	Description	Category	Number of Segments	Percentage (%)
Twltl_bin	Two-way left-turn lane	Present	696	3
		Not Present	22,940	97
Uv_cat_max	Maximal type/density of development	Urban Center	2,498	11
		Hub Urban Village	1,274	5
		Residential UV	3,106	13
		Not a UV	16,758	71
Speedlmt_cat	Speed limit (mph) [non-arterial streets, not posted at 25]	25	17,027	72
		30	5,715	24
		35	666	3
		40-45	154	0.7
		50-60	34	0.1
One_way	One-way traffic flow	Yes	1,425	6
		No	22,211	94
Thrln_cat	Number of thru lanes - thru-lane category	0 lanes (turns only)	2	~0
		1 lane	473	2
		2 lanes	21,137	89
		3 lanes	395	2
		4 lanes	1,286	5
		5+ lanes	141	1
Strippk_cat	Striped parking lanes	1 lanes	1,192	5
		2+ lanes	2,321	10
		No lanes	20,104	85
Adjacent_signal	Signal at adjacent intersections	1	2,374	10
		2	782	3
		0	20,652	87
ARTCLASS		Collector	2,260	10

Variable Name	Description	Category	Number of Segments	Percentage (%)
	Functional classification of roadway segment	Minor	2,488	11
		Principal	1,881	8
		Highway	31	0.1
		Local	16,961	72
		Missing	1	~0
Trancls_cat	Transit classification of roadway segment	Local, Temp, Restricted	231	1
		Minor	3,039	13
		Principal	1,999	8
		Undesignated	18,367	78
Bus_bin	Presence of bus lane	Present	209	1
		None	23,427	99
RTL_cat1	Presence of right turn lane(s) at adjacent intersections	1 adjacent int.	207	1
		2 adjacent int.	115	1
		None	23,313	98
LTL_cat1	Presence of left turn lane(s) at adjacent intersections	One intersection	661	3
		Both intersections	319	1
		None	22,655	96
LTL_cat2	Left-turn lane at either adjacent intersection	At least one	980	4
		None	22,655	96
TL_cat1	Presence of left or right turn lanes at adjacent intersections	Right turn lane(s) at one intersection	91	0.4
		Left turn lane(s) at one intersection	537	2
		Right turn lane(s) at both intersections	99	0.4
		Left turn lane(s) at both intersections	311	1
		Both left and right turn lanes at same intersection	71	0.3
		Both left and right turn lanes at opposite intersections	35	0.1
		Left and right turn lanes at both intersections	26	0.1
		No left/right turn lanes at adjacent intersection	22,465	95

Variable Name	Description	Category	Number of Segments	Percentage (%)
TL_cat2	Presence of either left or right turn lanes at either adjacent intersection	1 intersection	699	3
		Both intersections	471	2
		Neither	22,465	95
Sidewalk	Sidewalk presence on roadway segment	1 side	2,533	11
		Both sides	15,340	65
		None	5,763	24
NATIONHWYSYS	National Highway System Designation	Yes	1,854	8
		No	21,768	92
		Unknown	14	0.1
Bike_markings	Presence of any type of bike facility marking	1 side	701	3
		Both sides	1,056	4
		None	21,879	93
Bklane_cat	Presence of bike lane	1 side	685	3
		Both sides	543	2
		None	22,408	95

MODEL DEVELOPMENT

Researchers have used a variety of types of analyses to enhance understanding of pedestrian crash and injury risk. NB regression methods are typically used to identify a set of variables that combined, are predictive of crash risk. NB methods can handle the non-normal distribution of crash count data (HSM 2010, Vol. 1, p. 3-17). This analysis approach uses counts of pedestrian (or other type) crashes at each location of the "reference facility" type as the dependent variable. Variables of interest that may affect the frequency of pedestrian collisions are aggregated to each location and tested for significant contributions to crash prediction (given other variables in the model), often starting with a baseline model that incorporates traffic and pedestrian volume.

Two types of analyses were conducted (a regression tree analysis to first identify the most important predictors, and then SPFs were developed using NB regression). The analyses are described further below.

Conditional Random Forest Analysis

For both crash types, there were 51 potential explanatory variables. Many of these variables were potentially interrelated, so a data mining algorithm that can help identify the most important independently predictive variables among a correlated set of variables was useful to select a smaller set of variables to test in regression modeling. Conditional random forest (CRF) regression is a data mining method used to identify links between predictor and outcome variables within a data set. CRF can handle correlated predictor variables, and the outputs provide a relative importance ranking of statistically significant predictors of the outcome variable.

The means by which the CRF process determines potential significance of variables is through the development of many "crash trees," essentially predictive branches of interrelated variables. The crash trees are built by randomly and repeatedly subsampling data without replacement. Then the variable importance is calculated from the built trees. This procedure was conducted using Package "party" in R, and 1500 trees were developed for both crash models. These methods are described in more detail in Thomas et al. 2017. After this analysis, statistically-significant predictors were added to and tested in regression models in the order of importance indicated by the CRF outputs. In the CRF analysis, the team did not identify the direction of each variable's relationship with crashes (whether positive or negative)—only that it was an important predictor of pedestrian crashes. The relationship was only determined for the variables that remained statistically significant in the final SPF or negative binomial regression model, developed in the next step.

Regression Models

NB regression modeling was used to develop the two safety performance functions. Negative binomial regression is preferred when there are large zero counts in the data, resulting in a larger variance than mean. A few cleaning operations and transformations were used on the data prior to the NB regression analysis. For example, freeway observations (which primarily included ramps), were removed from the data since freeways are not typically crossed by pedestrians. Exposure values, such as AADT and AADP were tested using both raw estimates and logarithmic transformations (ln) in an attempt to identify the most accurate functional form for crash prediction. The untransformed AADT values were also rescaled by dividing by 10,000 to bring values more in line with log-transformed values. Mean income was also rescaled to get greater precision in variable estimates.

Analysts used the Proc Genmod procedure in SAS software to fit the crash prediction models. The CRF analysis, discussed in greater detail in the following section, identified 36 potential variables for the PMV_Strt model and 35 variables for the PedDark model. Due to concerns over model convergence and too many variables, variables were entered into the model on a one-by-one, forward regression process in their order of importance from the CRF analysis. Only variables with significant p-values ($p < 0.05$) were retained. Goodness of fit was also tested using Akaike's information criterion (AIC) and the Bayesian information criterion (BIC) (Akaike 1973; Schwarz 1978). The criteria are:

$$AIC=2k - 2\ln(L)$$

$$BIC=k\ln(n) - 2\ln(L)$$

Where:

- k = number of free parameters in the model;
- n = sample size; and
- L = maximized value of the likelihood function.

Superior model fit is indicated by a lower criterion value. The key difference between the two criteria is that the AIC does not account for sample size while the BIC does, essentially assigning a penalty for models with more parameters. Therefore, better models are those with lower criteria values and fewer parameters. However, for the purpose of this systemic study, the final models may retain more variables if these variables help to better explain risk to pedestrians. The final models were selected based on low AIC values and comprehensive, systemic variable inclusion, thereby, avoiding the penalty imposed on variable count by the BIC.

4.3 Results and Discussion

Figure 3 shows the importance ranking for variables tested for use in the PMV_strt model, and Figure 4 shows the importance ranking for the PedDark model. All variables to the right of the dashed line have some predictive power but that ability decreases the farther down the y-axis variable appears. The rankings do not indicate whether the relationship is positive or negative or curved. Most of the significant variables shown in the regression trees for both models were tested in negative binomial regression.

However, the team eliminated transit_stops_500_ft, pred_rfr, transit_stops_1000_ft, quart_comm, transit_stops_half_mi, closest_dist_univ (a very similar measure to univ_dist), quart_bus, connected_node_ratio, and tenth_pop variables from the PMV_Strt collision regression modeling in order to avoid multi-collinearity issue (i.e., the presence of transit stops influencing the model both as transit_stops_150_ft and transit_stops_500_ft). Since transit_stops_150_ft showed the strongest relationship to crashes, that measure was used. In each case, where there were measures at different scales of the same variable, the most predictive version was selected for further testing in regression models. Similarly "redundant" variables were eliminated from the PedDark collisions regression modeling, including quart_comm, transit_stops_500_ft, transit_stops_half_mi, transit_stops_1000_ft, max_slope_pct, and closest_dist_univ.

Analysts tested all of the remaining significantly predictive variables from the CRF analyses in regression models using the SAS Proc Genmod procedure. Variables that did not meet a significance level of 0.05 were considered poor predictors and removed from the models. As mentioned, AIC values were used to select the model with the best fit. A further check was applied to specific variables to test functional form; cumulative regression (CURE) curves were simulated for all numeric variables to determine if variable transformations (i.e., log transformation, quadratic transformation, etc.) need be used. These CURE plots were checked for clear trends and low p-values; p-values in the significant range ($p < 0.05$) may indicate that the variable form has been mis-specified. However, the CURE plots revealed no issues with variable misspecification, so no additional transformations (than those already mentioned) were required.

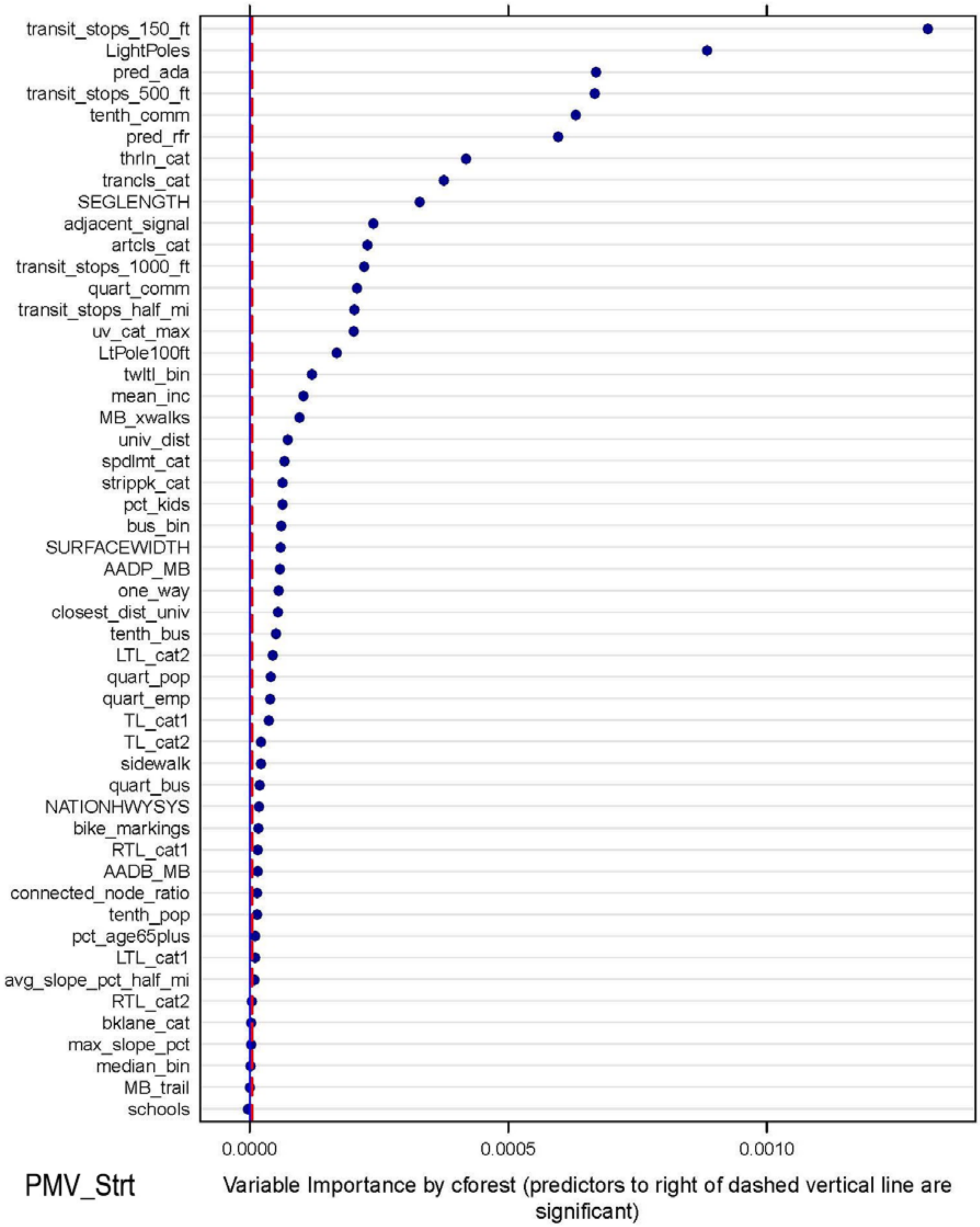

Figure 3. CRF variable importance for PMV_Strt model.

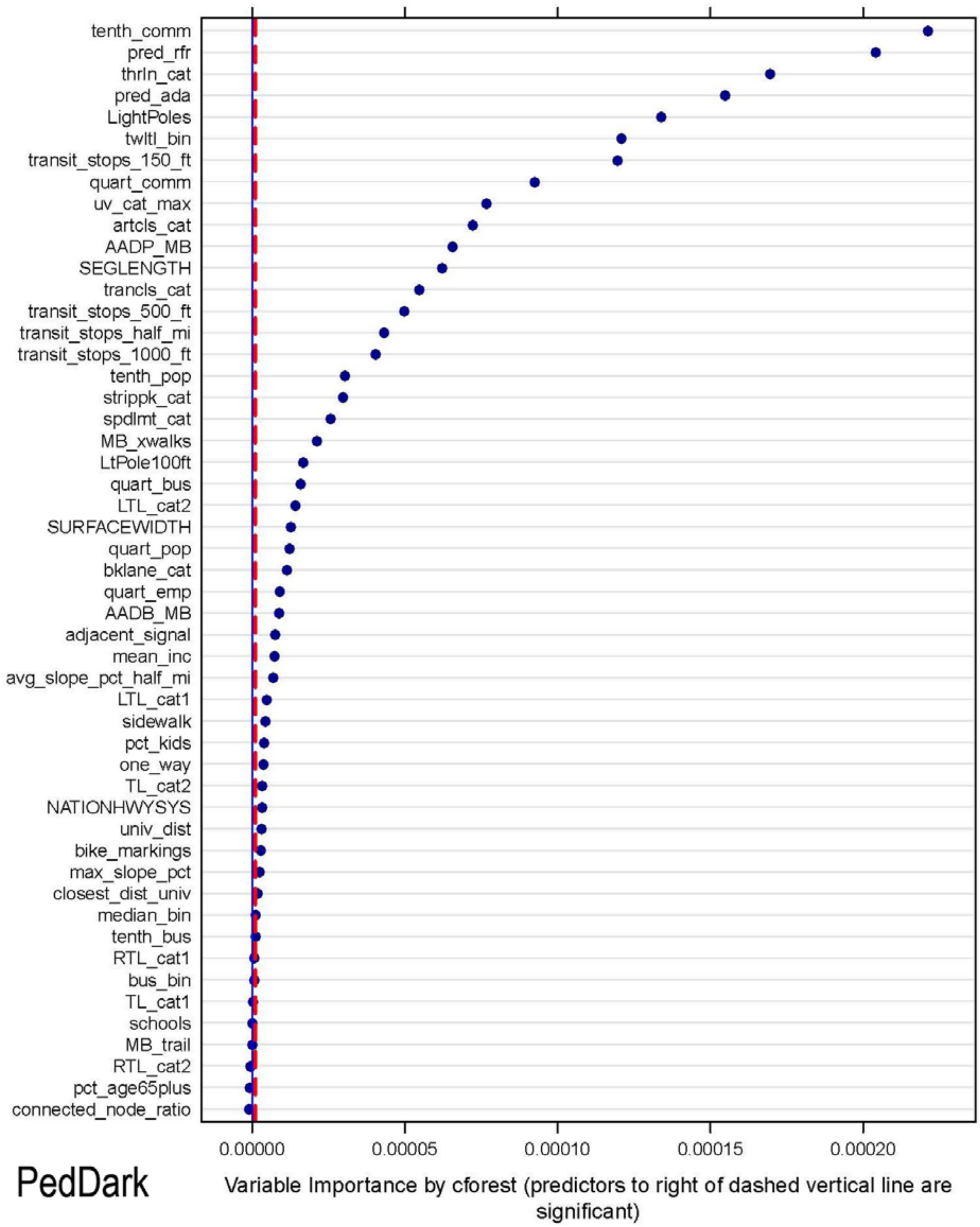

Figure 4. CRF variable importance for PedDark model.

The final models are shown below.

Analysis #1: Total Collisions between Vehicles Traveling Straight and Pedestrians at Segments (PMV_STRT)

The SPF is:

Eq. 1: Y(PMV_strt) = Exp(b0 + b1transit_stops_150_ft + b2LtPole100ft + b3Logpred_ada + b4tenth_comm + b5thrln_cat + b6uv_cat_max + b7twltl_bin + b8inc_s + b9MB_xwalks + b10strippk_cat + b11RTL_cat1 + + b12AADP_MB + b13 Logpeds)

Analysis #2: Motor Vehicle Collisions with Pedestrians at Night (PedDark)

The SPF is:

Eq. 2: Y(PedDark) = Exp(b0 + b1tenth_comm + b2pred_rfr_s + b3LtPole100ft + b4twltl_bin + b5transit_stops_150_ft + b6uv_cat_max + b7spdlm_cat + b8MB_xwalks + b9inc_s + b10one_way + b11AADP_MB + b12 Logpeds)

The model fit statistics for PMV_Strt and for PedDark are shown in Table 17. All variables shown are significant at a minimum of $p = 0.05$ level. For categorical variables, the significant categories are compared to the base category.

Although the data initially featured 23,897 observations, 261 were dropped to eliminate freeways/freeway off ramps from the data. No pedestrian segment crashes had occurred at these locations. Of the 23,636 observations remaining for the PMV_strt model, 23,147 were used due to cases with missing values for important predictors being dropped by the analysis. Of the 23,636 observations available in the PedDark model, 23,298 were used for prediction. For example, although surface width appears in the list of significant predictors in the CRF analysis, nearly 20 percent of all cases and 24 percent of local streets were missing data for this value and this variable was not selected in the regression models.

As can be seen in Table 17, a number of scalar variables exerted significant influence over the number of PMV_Strt crashes and PedDark crashes. To develop predictions for each observation, for scalar variables, the actual variable value (i.e. x_1=AADP_MB =2900) is multiplied by the coefficient estimate found produced by the statistical model (i.e. β_1=AADP_MB estimate=0.0002), and this product is added into the prediction equation. For categorical variables, the estimate value developed from the statistical model is added or subtracted based on the variable category level and level significance. For example, if the two-way, left-turn lane variable category is 1 (i.e. presence of a TWLTL), then the estimate value is 0.3511, and for this entity, this value is added to the crash prediction equation.

Both models included at least one term for vehicular volume and both the log-transformed and raw frequency terms for pedestrian volume. Comprehensively, these variables indicate that both vehicular volume and pedestrian volume are statistically significant for predicting crashes, consistent with prior similar analyses. For the PMV_Strt model, the logarithmic transformation of scaled, ADA-boosted AADT provided a better fit, as suggested by its higher importance ranking in the CRF analysis, and in the PedDark model, the scaled random forest-boosted AADT estimate (Pred_rfr/10,000) provided better crash prediction as also indicated by the CRF importance ranking.

Table 17. Final model statistics for crashes between motor vehicles traveling straight striking pedestrians on segments (PMV_strt), and crashes under dark conditions on segments (PedDark).

Variable Name (Description)	Category	PMV_strt			PedDark		
		Est.	Coef.	StdErr	Est.	Coef.	StdErr
Intercept	n/a	$b0$	-0.9796	1.2252	$b0$	-3.6968^{i}	1.6589
Transit_stops_150_ft (Daily buses within 150ft)	n/a	$b1$	0.0014^{iiii}	0.0003	$b5$	0.0013^{iiii}	0.0003
LtPole100ft (Light poles per 100 ft on segment)	n/a	$b2$	0.2018^{ii}	0.0624	$b3$	0.1783^{i}	0.0789
Pred_rfr_s (Predicted AADT = pred_rfr/10,000 estimate)	n/a		n/a		$b2$	0.4786^{iiii}	0.0715
Logpred_ada (Predicted AADT = Log transform of pred_ada estimate)	n/a	$b3$	0.5691^{iiii}	0.0582	n/a		
Tenth_comm (Commercial properties, 0.10 mi)	n/a	$b4$	0.0250^{iiii}	0.0043	$b1$	0.0300^{iiii}	0.0057
Thrln_cat (Thru-lane category)	0 thru lns 2 lanes 3 lanes 4 lanes 5+ lanes 1 lane (base)	$b5$	-16.3131 0.0126 -0.1890 0.5637^{i} 0.8373^{i}	18960.73 0.2416 0.2949 0.2621 0.3327	n/a		
Uv_cat_max (Urban village type of development)	Urban center Hub UV Residential Not a UV (base)	$b6$	0.7365^{i} 0.4195^{i} 0.4962^{i}	0.1604 0.1571 0.1203	$b6$	1.0071^{iiii} 0.5386^{i} 0.5187^{ii}	0.2206 0.2189 0.1722
Twltl_bin (Two-way left-turn lane present)	Yes No (base)	$b7$	0.3511^{ii}	0.1248	$b4$	0.6253^{iiii}	0.1525
Spdlmt_cat (Speed limit category)	30 35 40-45 50-60 25 mph (base)	n/a			$b7$	1.2872^{iiii} 1.6719^{iiii} 0.1883 1.5074	0.1785 0.2691 0.5359 1.1217
Inc_s (Mean Income area residents/10000)	n/a	$b8$	-0.0973^{iiii}	0.0172	$b9$	-0.0750^{ii}	0.0240
MB_xwalks (Midblock crosswalks count)	n/a	$b9$	0.8628^{iiii}	0.1704	$b8$	0.9031^{iiii}	0.2063
Strippk_cat (Striped parking lanes)	1 lane 2+ lanes No (base)	$b10$	0.4925^{iii} 0.3297^{ii}	0.1309 0.1085	n/a		
One_way (One-way traffic flow)	Yes No (base)	n/a			$b10$	-0.5942^{ii}	0.1913

Variable Name (Description)	Category	PMV_strt			PedDark		
		Est.	Coef.	StdErr	Est.	Coef.	StdErr
RTL_cat1 (Right turn only lane/lanes present at adjacent intersections)	1 adj. int 2 adj. int None (base)	$b11$	0.5850[ii] -0.2796	0.1847 0.3466	n/a		
AADP_MB (Midblock pedestrian volume along segment)	n/a	$b12$	0.0002[i]	0.0001	$b11$	0.0003i	0.0001[i]
Logpeds (Nat. log transformed AADP_MB)	n/a	$b13$	-0.7079[iii]	0.1949	$b12$	-0.6674[ii]	0.2745
Scale (Dispersion parameter)			1.2048	0.2156		1.2124	0.3644

[i] Significant at $p < 0.05$; [ii] $p < 0.01$; [iii] $p < .001$; [iiii] $p < 0.0001$

In both the PedDark and PMV_strt models, AADP_MB, a pedestrian volume estimate for the number of pedestrians walking along the segment, was statistically significant and positively correlated with pedestrian crashes. Both models included a second logarithmic transformed AADP_MB variable. This term, however, was found to be negatively associated with pedestrian crashes in both PMV_Strt and PedDark models. Taken together, these results are suggestive of a nuanced relationship between pedestrian volumes walking along the roadway and crashes involving pedestrians crossing the road. The relationship suggested that as the number of people walking along the roadway increased, crash risk tended to decrease (all else being equal).

These crash types, and even more diverse types of crashes occurring at night, are likely mediated by land uses, pedestrian attractors, and roadway characteristics. It would be optimal to have estimates or counts of pedestrians crossing anywhere along the segment, but, even in the most optimal situation, this level of data on crossing activity is likely unavailable. Thus, the use of volume estimates for pedestrians walking along the roadway, combined with other measures of the built environment and pedestrian attractors were both used to help estimate crash risk. A similarly nuanced relationship, with overall crash risk tending to decline above a certain volume of pedestrians, was also found in earlier analyses of pedestrian intersection crashes using Seattle data (Thomas et al. 2017). As noted in the introduction, many other researchers have documented a non-linear relationship between pedestrian crashes and pedestrian volumes (Lyon and Persaud 2002; Jacobsen 2003; Geyer et al. 2006). These findings reinforce the need to model this relationship to estimate other crash risks. The volume of bicyclists along these segments did not provide additional prediction of pedestrian crashes with the other variables that were included in these models.

Several other explanatory variables were significant in both models. One of these variables, transit activity (average daily numbers of buses stopping nearby), showed a positive association with increased collisions in both the PMV_strt model and the PedDark model. The effect was slightly greater for PMV_Strt, perhaps reflecting a larger amount of bus activity during the day and crossing activity associated with transit. Transit activity was also indicated to have the strongest predictive relationship with PMV_Strt crashes in the CRF analysis. This effect may relate to crossing activity that is not captured by the pedestrian volume (walking along roadway) estimates and may also include risks associated with how pedestrians behave as they cross streets to catch buses (dart across, etc.), as well as potential maneuvers by motorists weaving around buses, and issues such as sight distance/visibility when buses are at transit stops.

The amount of commercial development within 0.10 mi. was also significant in both models. This variable indicates that as the density of commercial establishments increases near pedestrian crossings, the likelihood of a pedestrian collision increases. This variable likely indicates that commercial properties act as pedestrian attractors, thereby increasing risk, but may also capture other elements of the urban environment that influence pedestrian crash risk. These elements could include how pedestrians interact with the road network, for example in areas of dense urban nighttime activity.

Other variables positively associated with frequencies of both crash types included the presence of one or more midblock crosswalks along the segment, and the frequency of light poles along the segment. Both of these measures are likely also capturing exposure, in part. Since there were no specific estimates of pedestrians crossing at segments (only estimates for the numbers of pedestrians walking along the roadway were available), the crosswalk variable is likely associated with the missing data on crossing volumes but may capture other unknown types of risk as well. It is intuitive that midblock crosswalks have been installed where there is significant pedestrian demand and there will be higher levels of midblock crossings at such locations thereby exposing more pedestrians to potential for collisions. It should be noted that midblock crossings themselves do not necessarily increase risk. They merely act as the points at which pedestrians are more likely to be. However, these results suggest there may be a need for additional improvements to reduce risks at uncontrolled but marked crossing locations.

The rate of light poles per segment distance was also positively related to crashes, which is counter-intuitive. However, the rate of the number of light poles does not necessarily reflect the lighting quality or intensity in the pedestrian environment. This result may also reflect an "endogeneity" issue with lighting; that is, lighting was installed where crash risk was higher. Finally, this finding suggests the importance of conducting controlled, before-after evaluations of lighting improvements to assess the safety effects.

Mean income had a negative association with pedestrian crashes in both models, so as income of residents in the area increases, crashes tend to be lower. This finding may indicate a relationship between walking as a means of transportation and income, providing a further enhancement to exposure estimation, as well as other possible population-built environment factors and infrastructure differences among neighborhoods that are not completely captured by the variables available.

A number of categorical variables related to the built environment were associated with both types of crashes. Both the PMV_strt and the PedDark models had positive associations with the city's urban village designations, which are reflective of development intensity. In fact, all three levels of the variable above the base were significant. This variable is another built environment measure that seems to show that as the density and type of development increases, more pedestrians are exposed to crashes. Several urban villages in Seattle are also centered around universities and residential areas that generate and attract significant pedestrian foot traffic.

Accounting for traffic volume and activity-based risk exposure in the models, several roadway factors also contributed significantly to crash prediction, suggesting additional risk posed by these characteristics. Among roadway factors, both models showed positive associations between collisions with pedestrians and the presence of a two-way left-turn lane. This variable records the presence of a TWLTL in addition to the number of thru lanes captured by the thru lane variable. TWLTLs could increase risk in several ways: exposure to an additional lane where drivers may be focusing on left-turn maneuvers; the total crossing distance is increased; there may be increased conflicts all along the segment since turns may be made anywhere there are intersections or driveways; and pedestrians may be induced to cross such streets, thinking that the TWLTL acts as a refuge area between opposing lanes of traffic. The relationship was stronger in the model of nighttime crashes (which also included turning crashes). At night, pedestrians may not be seen by drivers due to glare of oncoming headlights regardless of whether they are in through lanes or in the center turn lane at the time of the collision. A closer look at this variable showed that road segments with TWLTL accounted for 2.9 percent of the total number of road segments, but 16 percent of the total number of PMV_Strt collisions, and 20.1 percent of PedDark collisions.

Note that after initial analyses were performed, with results almost the same as those reported here (except for slight differences in coefficients), conversations with city staff revealed that the city had implemented 18 road diets within the crash analysis study period. Many of the road diets changed whether or not a TWLTL was present, and the number of through lanes – variables that were found to be significant in one or both models – and which could therefore potentially confound our results. Since our roadway data were based on a “snapshot” of characteristics associated with roadways near the end of the study period (from 2013-2014), the project team updated the data and created observations for before and after periods so that the crashes would be associated with the correct configuration. The re-analyses are reported here, and these corroborated the initial findings.

Specific to the PMV_strt crashes were associations with increasing numbers of thru-lanes, striped parking lanes, and right-turn lanes at adjacent intersections. Compared to only one thru-lane, roads with four, or five or more through lanes were significantly associated with more pedestrian collisions compared with one lane; roads with two or three through lanes were not significantly different from one through lane (with three lanes showing a non-significant, negative association). This association was not detected for PedDark collisions, perhaps owing to a smaller sample size or for other reasons.

The presence of striped parking, whether just one lane or two or more lanes, was also positively associated with PMV_Strt collisions with pedestrians, but not the nighttime collisions. This result may indicate potential conflicts between pedestrians and vehicles on busy arterial/collector streets with striped parking, as well as potential for visibility issues.

The last categorical variable associated with increased PMV_Strt collisions is the presence of one or more right turn lanes at one of the adjacent intersections compared to a no right-turn lane. Interpretation of this relationship is not entirely clear, but it may suggest that risks related to driver turning movements on approaches to or leaving a neighboring intersection may affect pedestrians crossing along the segment, including, as defined in this study, just outside the crosswalk area (but within the segment). A potential lack of driver anticipation of pedestrians crossing outside of the intersection/crosswalk area, and/or lane-changing behaviors on approaches to an intersection could generate additional conflict and risk for pedestrians crossing away from the intersection. The presence of right turn lanes and significant turning traffic could also affect pedestrians’ perception of safety in crossing at the adjacent intersections and induce them to attempt crossing away from the intersection (along the segment) instead.

Specific to the PedDark model were associations with speed limit categories and one-way streets. Compared to the base speed limit of 25 mph, both 30 and 35 mph speed limits were significantly associated with increased pedestrian collisions at night. (Increasing trends for even higher speed limits were not statistically significant, but there were relatively few segments with these higher limits in the dataset.) These results could indicate increased difficulty for drivers to react appropriately to pedestrians crossing midblock at night due to higher travel speeds or traffic density may be lower at night so that speed limits better capture risk related to maximum limits. However, note that speed limits were also highly correlated with arterial classification, with all undesignated (local) streets having statutory 25 mph limits during this study period. Arterial classification was also tested in the modeling process and with these other explanatory variables in the models did not contribute significantly to crash prediction. The lack of significance of speed limits in the model of PMV_Strt crashes may suggest that during daytime, actual travel speeds could be more limited by congestion and speed limit may not serve as an adequate measure of risk associated with speed.

One-way streets, compared to two-way streets, were negatively associated with pedestrian collisions at night. This result could relate to the fact that pedestrians only have to focus their attention on crossing one traffic direction at a time, resulting in a protective factor for the pedestrians. It may also possibly relate to the fact that drivers would not have to face opposing traffic and headlight glare and may be better able to see pedestrians at night on one-way roads.

While appearing to be related to crash risk from the CRF analysis, segment length did not remain in either SPF with the other variables that were selected. Sidewalk presence was not a strong predictor of crashes in Seattle; this may be because the city is fairly built out in terms of sidewalks (76 percent of all segments), and the vast majority of segments lacking at least one sidewalk (87 percent) were local streets. In other cities with less infrastructure, sidewalks may be a more important pedestrian crash predictive factor.

4.4 Summary and Implications for Systemic Pedestrian Safety Process

The foregoing discussion highlights findings from the final SPF models. The discussion also highlights some issues for consideration by analysts when determining risks factors to use in screening. Most of the factors from this analysis have plausible associations with crash occurrence based on increases in pedestrian activity, exposure to traffic volumes, exposure to roadway-based conflicts and complexity, and traffic speed. One exception is the density of light poles per distance being positively associated with crashes. This finding is counterintuitive and suggests that light poles may have been added to segments where crash risks were higher (known as an endogeneity issue); this surmise was supported by SDOT staff. This variable may also reflect other information about the roadway or environmental crash risks that remain unobserved or unmeasured (possible missing variables). Thus, we would not assume that identifying segments with the most light poles and removing them would reduce crash risk. However, for whatever reason, this element helped to predict where crashes have occurred, and thus, may be useful in the model for its role in crash prediction. Other analysts may choose to remove such a variable from the final model.

The factors in the model that have a logical relationship to crash frequency—*and* are related to "treatable" roadway characteristics and potential countermeasures—were identified. The below factors can also be associated with potential systemic treatments. These include:

- Presence of TWLTLs, which were significant predictors for both types of crashes;
- Presence of a midblock crosswalk (both models);
- Larger numbers of lanes (four or five or more);
- Presence of on-street striped parking (which is associated with non-local street types);
- Presence of right-turn-only lanes at an adjacent intersection; and
- Speed limits above 25 mph.

In addition, traffic and pedestrian volumes, commercial land use, and transit activity provide important context for selecting the appropriate countermeasures. One-way traffic flow was negatively associated with nighttime crashes and could potentially be considered 'protective' against pedestrian nighttime collisions.

The results of these analyses are used in the *Systemic Pedestrian Safety Analysis Guidebook* to flesh out examples of screening, countermeasure selection, and prioritization. in examples of screening based on the appropriate risks identified, matching risks and locations with appropriate potential countermeasures, and prioritizing a treatment package based on expected crash savings and countermeasures costs

As mentioned in Chapter 3, besides their use to identify factors associated with pedestrian collisions, another value of developing SPFs is that the crash prediction estimates available from the model outputs are useful to prioritize sites that may be most likely to experience future crashes, and to perform cost-effectiveness assessments. Figure 5 shows a capture of a portion of a spreadsheet that contains all of the observed values for the variables in the PMV_Strt SPF for each segment. The model equation can be used to calculate estimates of crash potential for each site, based on the site characteristics. Using equation 1 for the PMV_Strt SPF, the columns such as twltl_bin (two-way left turn lane) and Thrln-cat (number of through lanes) contain the data (observed condition) and the coefficients (TWLTL_co; THRLN_co), for each variable,. Scalar variables such as the logadta value are multiplied by the coefficient (LNADT_co), whereas the coefficient is added to the prediction for the given significant levels of categorical variables such as Thrln_cat (number of through lanes; THRLN_co value of 0.5637 is added for values of 4). Finally, since the equation is a log equation, the exponent of the sum of all the individual values is calculated. The first highlighted column shows observed crashes, and the next three highlighted columns show three types of estimated crashes (SPF-predicted, EB and Excess) resulting from the model prediction equation. The formula for calculating the predicted crashes (SPF-pred) from the model is illustrated in the formula bar. The EB estimate is calculated from a weighted average of the observed crash count at each site and the expected number of crashes based on the SPF and these equations are available in the HSM and other resources.

These predictions may in turn be used to rank locations according to these estimates of crash potential. The predicted crashes, weighted prediction, or excess expected crashes (SPF, EB, or Excess expected crashes, which = EB - SPF) can be used in economic analyses to prioritize systemic treatment packages. The Guidebook provides illustration of these uses.

=EXP(-0.9796+(B2*C2)+(BS2*BT2)+(V2*W2)+(AS2*AT2)+(BK2*BL2)+(AG2*AH2)+(AD2*AE2)+(D2*E2)+(CL2+CA

AE	AS	AT	CK	CL	CO	CP	DI	DK	DQ
MBX_co	logadta	LNADT_co	Thrln_cat	THRLN_co	twltl_bin	TWLTL_co	PMV_Strt	SPF-pred/year	EB/year
0.8628	0.690444	0.5691	4	0.5637	0	0	3	0.06987	0.19266
0.8628	-1.59258	0.5691	2	0	0	0	0	0.00264	0.00257
0.8628	0.804778	0.5691	4	0.5637	1	0.3511	0	0.03836	0.02800
0.8628	0.690444	0.5691	4	0.5637	1	0.3511	2	0.09603	0.17004
0.8628	-2.04028	0.5691	2	0	0	0	0	0.00298	0.00289
0.8628	-2.22008	0.5691	2	0	0	0	0	0.00096	0.00095
0.8628	-1.72822	0.5691	2	0	0	0	0	0.00392	0.00378

Figure 5. Spreadsheet showing some observed values for significant factors and predictions for PMV_Strt pedestrian crashes at specific segments.

STUDY LIMITATIONS

The primary limitation to the study findings is that the data analyzed represent one large urban jurisdiction and may not reflect conditions present in other jurisdictions. Although the data are specific to one jurisdiction, the database included numerous potential risk variables for all road type segments (nearly 24,000) throughout the city across varied land use types and population densities. Nevertheless, the ranges of values may be dissimilar to other jurisdictions with lower (or higher) densities and different network characteristics. In addition, the estimates of pedestrian volume – for walking along a section – were not ideal for assessing exposure to crashes involving pedestrians crossing or being in the road at midblock locations. However, the measures did prove to contribute to crash prediction in the models, along with other measures of the built and social environment that represent pedestrian attractors.

Measurement and analysis of risk is also an imperfect science, as demonstrated by the apparent positive relationship of light poles to pedestrian crashes. This finding may merit further investigation. In addition, the results point to a continuing need to diagnose individual locations and pedestrian-motor vehicle interactions, whether locations are prioritized through a systemic screening or high crash screening process. Even if particular crash types or risks are accounted for in an analysis, risk measurement or crash prediction is based on imperfect data and imperfect analyses, and individual locations may have either common, but unmeasured, or site-specific conditions that contribute to crash risk.

This type of analysis necessarily excludes some risk factors that are directly associated with crashes or injury severity including pedestrian or driver impairments and behaviors, ages of drivers or pedestrians (which may be associated with mobility), as well as specific events leading up to crashes. However, in partial consideration of different types of severity-based risk, the team was able to analyze two specific crash types, including crashes at night, and midblock crashes involving through motor vehicles, both of which tend to have a higher proportion of severe outcomes. The team also incorporated socio-demographic measures (pedestrian age groups, income, etc.) into the data associated with locations, while acknowledging that measures of population factors around walking locations may not fully reflect who is actually walking there. Nevertheless, these findings further the state of knowledge of potential pedestrian crash risks for segment or uncontrolled crossing locations. Agencies with a high proportion of crashes involving seniors or younger pedestrians could also count these types to perform an analysis of crash frequency factors.

CHAPTER 5: Identifying Systemic Pedestrian Countermeasures

The purpose of this chapter is to outline the research process, selection criteria, and application considerations for treatments recommended as potential systemic pedestrian countermeasures. The Guidebook describes the recommended countermeasures, their effectiveness, and their application in a systemic pedestrian safety process.

5.1 Research Methods

To identify an initial comprehensive list of potential countermeasures for which to apply the selection criteria (described in the next section) project team members drew from several previous comprehensive literature reviews:

- NCHRP 15-63: Literature Review of Pedestrian and Bicycle Countermeasures at Intersections (Nordback et al. 2017);
- Development of Crash Modification Factors for Uncontrolled Pedestrian Crossing Treatments. Pre-publication draft of NCHRP Research Report 841 (Zegeer et al. 2017a) and related Transportation Research Record article (Zegeer et al. 2017b);
- NCHRP Synthesis 498: *Application of Pedestrian Crossing Treatments for Streets and Highways* (Thomas et al. 2016);
- *Evaluation of Pedestrian-Related Roadway Measures: A Summary of Available Research*, for the Federal Highway Administration (Mead et al. 2014);
- *PEDSAFE: Pedestrian Safety Countermeasure Selection System* (2013);
- NCHRP Report 674: *Crossing Solutions at Roundabouts and Channelized Turn Lanes for Pedestrians with Vision Disabilities* (Schroeder et al. 2011);
- Transit Cooperative Research Program (TCRP) 112/NCHRP 562: *Improving Pedestrian Safety at Unsignalized Crossings* (Fitzpatrick et al. 2006);
- *Designing Walkable Urban Thoroughfares: A Context Sensitive Approach* (Institute of Transportation Engineers (ITE) 2010);
- *Safety Effects of Marked Versus Unmarked Crosswalks at Uncontrolled Locations: Final Report and Recommended Guidelines* (Zegeer et al. 2005); and
- *Toolbox of Countermeasures and Their Potential Effectiveness for Pedestrian Crashes* (2013).

In addition, the team searched the UNC-HSRC maintained CMF Clearinghouse, a searchable website database of studies that have measured countermeasure effects on crashes of all types. The team also performed an updated search of Transport Research International Documentation (TRID) and Transportation Research Information Services (TRIS) and other citation databases to identify peer-reviewed evaluation studies published in 2017 that were not identified in the earlier reviews.

This review culminated in a list of *all* pedestrian crash countermeasures that had CMFs or crash reduction evidence from one or more studies. The signal-related measures that were found to have safety benefits, (i.e., CMFs of < 1.0) include:

- Exclusive pedestrian signal phasing;
- Improved signal timing, including increasing pedestrian walking period;
- Replacing traditional pedestrian signals with the pedestrian signals with countdown timers;
- Modify signal phasing to a leading pedestrian interval;

- Removing unwarranted signals on one-way streets;
- Converting permissive left-turn signal timing to protected or protected/permissive;
- Use of the pedestrian hybrid beacons; and
- Installing traffic and pedestrian signals when warranted.

Geometric treatments which were found to reduce pedestrian crashes (CMF < 1.0) include:

- Narrow the roadway cross-section from four lanes to three lanes (two through lanes with a center turn lane);
- Install sidewalks or paved shoulders;
- Install raised refuge islands;
- Install a raised pedestrian crossing;
- Install raised medians at unsignalized crossings;
- Convert unsignalized intersection to a roundabout; and
- Install pedestrian underpass or overpass.

Sign, marking, and operational improvements having beneficial crash effects (CMFs < 1.0) include:

- Install intersection lighting;
- Add roadway section lighting;
- Improve pavement friction;
- Install advance stop/yield signs and pavement markings (between 20 and 50 feet in advance of the marked crosswalk) at uncontrolled pedestrian crossings
- Prohibit right-turn-on-red;
- Prohibit left-turns;
- Restrict parking near intersections;
- Provide high-visibility crosswalks; and
- Provide high-visibility crosswalks in school zones.

5.2 Systemic Countermeasure Selection Criteria

The project team applied the following additional criteria to countermeasures identified in the studies and list above to produce a shortlist of treatments with high potential for effective use in a systemic process:

1. **Safety effectiveness -** Preference was given to countermeasures with crash-based evidence of effectiveness for pedestrian safety. Crash-based evidence is often based on a few studies or lacking entirely, so other measures of effectiveness such as speed lowering effects, or significant improvements in motorists yielding at uncontrolled locations, were also considered. Speed is considered a good safety surrogate since it has documented effects on the frequency of fatal and injury crashes of all types (HSM 2010). Increasing impact speed is a relative risk for increasing pedestrian injury and fatality in the event of a crash (Rosén and Sander 2009; Tefft 2013; Kröyer et al. 2014). Design speed and other design factors related to risk principles (e.g., crossing distance, sight lines or conspicuity, and conflicts) were also considered in the selection of some treatments with less direct evidence of safety benefits.

2. **Cost effectiveness -** Cost-effective treatments are important for a systemic approach to achieve the expected safety benefits. If high-cost treatments are required, the approach may suffer from

similar limitations as traditional safety approaches, in that fewer sites may be treated without additional resources, leaving many untreated. The team therefore focused on countermeasures in the low-to-moderate cost range, since agencies may be able to implement these at more locations to potentially achieve greater benefits. The measures included can generally be implemented for around $100,000/site or less. Note, however, that more expensive design measures may have longer-term and more consistent benefits, and agencies may wish to consider these types of measures on a case-by-case basis or when other project opportunities arise.

3. **Feasibility for implementation at many locations -** The countermeasures included can potentially be implemented at many locations (with similar risk and roadway characteristics) through changes in signal timing and operations; addition of pavement markings, signs, and beacons; and relatively low-cost design changes (examples are the addition of median islands and raised traffic calming devices) and will not require additional right-of-way or complex inter-agency agreements. Some treatments, such as road diets, may require a public input process until they gain wider acceptance by the community.

The following 12 countermeasures were identified for potential systemic application:

1. High-visibility crosswalks
2. Median crossing islands
3. Reduce number of lanes/road diet
4. Site-specific lighting improvements
5. Advance Stop/Yield Bars and R1-5/5a signs
6. Pedestrian Hybrid Beacon
7. Leading Pedestrian interval
8. Longer pedestrian phase
9. Fully-restricted left turns/protected crossing phase
10. Raised traffic calming devices
11. In-roadway Yield-to-Pedestrian signs (r1-6/6A)
12. Curb extensions plus removal of parking

The Guidebook summarizes the available safety evidence for each countermeasure, the types of risks or crash patterns that are most likely to be affected by the treatment, and the general traffic context (speed and volume, number of lanes) in which the treatment may be most appropriate, based on current knowledge. While the latest information available on crash and safety effects was included, practitioners are advised to always check the resources listed in the Guidebook (the CMF Clearinghouse and others) for the most up-to-date safety effectiveness evidence for the most relevant type of application to that being considered. Descriptions of each treatments purpose, effectiveness and use in a systemic process are also provided in the Guidebook, and in Appendix A.

Beyond the 12 treatments listed, the team weighed other treatments known to be effective including sidewalks and pedestrian countdown signals (PCS). Many effective treatments, including these, are now treated as “systematic” countermeasures, or those that are routinely implemented system-wide as part of a standardized policy or design practice at appropriate locations. For example, pedestrian countdown signals are now standard practice for all *new* signalized intersections with pedestrian signals, per the MUTCD (2009). However, not all agencies may have fully upgraded or completed their existing facilities to incorporate sidewalks at all appropriate locations or PCS at all signalized intersections with pedestrian signals. Therefore, these two treatments—sidewalks and PCS—as well as ADA-accessible curb ramps, may be added to the list of treatments for systemic applications, and should certainly be applied in conjunction with the treatments listed above when they are not present but are needed for network completion.

Other treatments that agencies have identified as effective may be added to the systemic treatment options. These treatments may include both lower cost measures and higher-cost design treatments such as traffic circles, mini-roundabouts and roundabouts, or corridor-long medians with pedestrian crossings, especially if these can be justified through life expectancy and potential safety benefit calculations, and funds are available (Gross et al. 2016b). These types of measures may be further justified if they provide benefits to multiple modes and provide other benefits to the community as well. Examples include road diets (reduce total crashes), medians or median islands (reduce head-on motorist crashes), and separate left-turn phasing (reduces all types of left turn crashes at signalized intersections).

The latest version of the Manual on Uniform Traffic Control Devices for Streets and Highways (MUTCD) provides guidance and standard practices regarding the use of warning signs (and other traffic control devices), including when and how specific signs should be applied as companions to the treatments listed in the Guidebook. PEDSAFE (2013), an expert countermeasure selection guide, provides additional information about the treatments included in this Guide as well as many other potential pedestrian improvements.

5.3 Other Effectiveness and Implementation Considerations

Agencies may need to consider the following additional findings from syntheses of practices:

- Treatments may vary in effectiveness even when applied to broadly similar locations due to a variety of circumstances. Effects may vary by state, city, and location due to differences that are not fully understood but may include such regional difference as amount and effectiveness of enforcement, general driving and walking customs, and other factors (Thomas et al. 2016). Effectiveness may also vary from CMFs developed predominantly using high-crash sites (Gross, et al. 2016b). However, CMFs for pedestrian treatments under specific local conditions are difficult to produce, and the available CMFs may provide the best available estimates of expected crash effects, especially when treatments are implemented under similar conditions to the study conditions. Consideration can be given to the standard errors or confidence interval of the CMF estimates to provide 'best case / worst case' estimates of expected effect. Adjustments to CMF estimates may also be applied for use in economic analyses based on local knowledge and experience with a treatment. The CMF Clearinghouse, HSM, and other sources provide additional information on use of CMFs for benefit/cost assessment.
- Different agencies may consider applying the same treatments in different contexts. Local knowledge and engineering judgment must always be applied to final countermeasures decisions. Especially when considering different treatments or packages of treatments that require motorists yielding to pedestrians to work, experience or data regarding driver yielding rates, traffic volume, traffic speed, whether the location is used at night and well-lit, and other conditions should guide the final decisions.

A systemic approach is also a complementary part of a collaborative and comprehensive approach to pedestrian safety but will not replace these other efforts. As already mentioned, systematic efforts and policies and planning are the most proactive approaches to pedestrian safety. Setting of injury-reducing speed limits, law enforcement, and other community-based design programs also have a role to play. For example, automated speed enforcement (ASE) is an example of an enforcement program that might be expected to provide safety benefits to pedestrians when crashes are associated with exceeding limits and systemic treatments alone are insufficient to ensure compliance. ASE has been shown to reduce fatal and injury crashes of all types (Goodwin et al. 2015). Other efforts, such as coordinated traffic signal progression, might also help to manage speeds for certain signalized corridors and help to create gaps for pedestrians to cross between signalized locations.

As described in Step 4, traffic exposure is a key pedestrian crash risk factor. Although falling outside the list of systemic pedestrian safety treatments, there is also potential for reducing traffic impacts on pedestrian safety by providing more off-road and grade-separated facilities, or by restricting traffic in certain high pedestrian zones. For example, one approach to reduce pedestrian exposure to traffic is to provide pedestrian routes that bypass motor vehicle traffic. This may be in the form of neighborhood pedestrian paths and other connectors that allow some pedestrian trips to remain internal to a neighborhood, campus or business park, reducing the need for pedestrians to travel along busy streets. Providing pedestrian connections between adjacent cul-de-sacs in separate neighborhoods or streets could also reduce pedestrian exposure to traffic. Such measures may not be identified or implemented through a traditional systemic safety analysis and may require more community input into design and policies.

The above are just a few examples of a comprehensive approach to pedestrian safety that maximizes all opportunities to provide a safe and connected pedestrian network that minimizes pedestrians’ exposure to conflicts and potential crashes with motor vehicles.

CHAPTER 6: Discussion and Future Research Needs

The research summarized in this report describes the background and rationale for a risk-based approach to pedestrian safety analysis. A primary rationale for a systemic approach is to aid in identifying sites where crashes are likely to occur in the future, unless some physical roadway improvements are made. Furthermore, these high-risk sites should be identified and considered for improvement, not simply because they are associated with high levels of pedestrian and/or vehicle activity, but because they have certain high-risk roadway characteristics and/or land uses as well.

It is important to not rely solely on "high-crash" locations to identify potential risk factors associated with pedestrian collisions. This is because there may be other locations that have similar or even more unsafe roadway characteristics as the high-crash sites. If high-risk sites can be identified and treated appropriately, then pedestrian crashes may be avoided in future years. Reliable crash prediction estimates are needed to help identify and prioritize locations that should be treated, since many zero-crash (or low-crash) locations may be identified based on risk factors. In order to accomplish these objectives, there is a clear need to account for pedestrian activity and traffic volumes in analyses of risk. It may be preferable for agencies to identify their own high-risk features, but if this is not possible, this report and the accompanying *Systemic Pedestrian Safety Analysis Guidebook* offers factors that have been identified in safety literature and prior analyses.

As evidenced in Chapters 2 and 3, non-traditional data types have frequently been found to be associated with pedestrian crash risk. These include variables derived from existing data sets such as census data, land use data, and transit stop data, which are often readily available to agencies if minimal resources can be applied to compile and spatially link these data types to roadway databases. These data types may help to account for pedestrian activity and exposure to traffic risks, and for the complexity of ways in which pedestrians access and use roadways.

The systemic applications identified in Chapters 1 and 2, and further refined and developed in Chapters 3 and 4, illustrate the value of an approach that makes use of crash, roadway, traffic and pedestrian volumes, and other data from across the network. Such data can be used to perform an analysis that can simultaneously account for multiple potential risk factors. Identifying risk factors is challenging work, particularly given a historic lack of investment faced by many states in collecting data related to pedestrian volumes and facilities. At present, the most widely recognized pedestrian risk factors have been inferred from safety research studies that have employed types of crash prediction modeling resulting in the development of safety performance functions, which are crash prediction equations. The ability of an agency to predict where crashes might occur can be enhanced from an analysis approach that accounts for certain types of traffic and common built environment risks.

The state of practice and knowledge is evolving rapidly regarding identifying risk factors. It is also recognized that many state and local jurisdictions currently struggle with collecting, compiling, and analyzing the necessary data for pedestrian safety purposes, especially regarding the collection or estimation of pedestrian volume data. The problem is that agencies need information to help with pedestrian safety treatment prioritization since it seems clear that in a risk-based implementation program, many locations with zero prior crashes could be identified as candidates for treatment. It has been challenging, without proper data and analyses that account for motor vehicle and pedestrian activity, to determine which locations really should be treated, and to perform expected economic analyses. This can result in inaction for many problem sites with continued potential for pedestrian crashes in future years.

More agencies are looking for the safety and efficiency gains reaped by comprehensively assessing the network and applying relatively low-cost treatments to higher risk (higher crash potential) sites where safety improvement funds will do most good. A quantitative, systemic approach will support agencies in this effort, if the necessary data are collected and included in the analysis and prioritization processes. The effort may ultimately be streamlined if agencies are willing to invest in the beginning the process by collecting and compiling a robust database that includes estimates of pedestrian and motorized traffic volume for all locations, or reasonably good surrogate measures for these. The results can then be consulted in concert with other safety and project development activities. In other words, it may be wise for agencies to spend more time at the start of the process creating a robust data collection program, than to have to stop the process midway in order to gather the data necessary for effective decision-making.

Regarding evaluation, one research need, as mentioned in Chapter 5, is to evaluate the safety impacts of treatments in systemic applications. There is a possibility that crash reductions may be different than those expected based on CMFs that may have been developed using mostly higher crash sites. However, it should also be noted that crash reductions at any particular site may not need to be as high in more widespread systemic applications to achieve overall safety goals. In addition, the treatments featured in the Guidebook are by-and-large treatments that work by reducing "exposure" (crossing distance, number of lanes, etc.) or help to control traffic movements and speed, and so are expected to be effective in systemic applications over a longer time frame. There is, however, always a continuing need for more research into safety effects of more types of treatments. Systemic applications across multiple jurisdictions also offer an opportunity here since treatments may be implemented at more sites and become more widely documented. Some key treatments that could be priorities for CMF development include curb extensions and daylighting (removal of parking near crossing locations). Although these were deemed effective based on risk concepts and practitioner reports, CMFs would be useful to confirm safety benefits and accelerate safety decision processes. Pedestrian CMFs for other low-cost treatments such as right-turn-on red restrictions or "Yield to Pedestrians when Turning" signs would also be useful in a systemic approach.

There are several active research projects that relate to pedestrian safety and whose findings may inform future systemic analysis efforts. For example:

- FHWA Development of Crash Modification Factors (DCMF) Program Task B5 to evaluate leading pedestrian intervals (LPIs) and protected left turn phasing for pedestrian safety;
- FHWA DCMF Program Task A5 is evaluating pedestrian countdown signals in three cities: Toronto, Philadelphia, and Charlotte;
- NCHRP 07-25 *Guide for Pedestrian and Bicycle Safety at Alternative Intersections and Interchanges*; and
- NCHRP 17-84 Pedestrian and Bicycle Safety Performance Functions for the HSM update.

As more studies are conducted, there may also be a need to consider measurement and analysis approaches that can better account for more specific crash and severity risks. Examples include motorist speed and, potentially, pedestrian behaviors prior to the crash. For example, how can travel speeds or pre-crash speeds be measured in meaningful ways to assess pedestrian (and other modes') safety risk across the network or at different times? This report and the Guidebook describe some of the ways agencies have accounted for intrinsic crash risks that relate to severity of injuries. As the body of evidence grows, it will be important to revisit key assumptions and research underlying these documents and update them with the best available information.

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APPENDIX A: Survey on Systemic Practices

The following sections provide the electronic survey questions and a summary of the responses received.

Survey Questions

Introduction

This survey is specifically focusing on the application of "systemic approaches" to improving pedestrian safety. A systemic approach is one that seeks to proactively identify sites for potential safety improvement based on specific risk factors. These risk factors may be associated with a particular crash type or a grouping of crash types that are found widely or are spread across the network with few or no individual locations experiencing a high volume of crashes. This approach complements a more traditional approach that focuses on a site-specific analysis of high-crash locations (e.g., “hot spots”). A systemic approach examines crash, roadway, traffic and other network data to identify 1) risk factors associated with a particular crash type, 2) locations where those risk factors exist on a system, and 3) countermeasures that can be implemented across those locations to mitigate the associated risk factors. An example of a systemic pedestrian safety improvement process would be a study to identify risks associated with midblock pedestrian crossings, and application of remedies to reduce exposure to those risks such as pedestrian median islands and others.

Using a systemic approach and the analysis of aggregate data across a network may be especially important for preventing future pedestrian crashes. Pedestrian crashes may not be concentrated at any one specific site but may have recurring types with common contributing risk factors that could be treated with a similar set of safety improvements.

Systemic Approach to Improve Pedestrian Safety* My organization has experience using a systemic approach to improving pedestrian safety

- ○ Yes
- ○ No
- ○ I don't know

Involvement in Systemic Pedestrian Safety Improvements

Has your organization undertaken any of the following activities related to their involvement with systemic pedestrian safety improvements? (mark all that apply)

- ☐ Identifying common “risk factors” that may be contributing to crashes (e.g., high speed limits, high traffic volumes) using prior research or your own data or other methods
- ☐ Identifying locations where risk factors are present (even if they have not experienced a high number of crashes)
- ☐ Identifying particular safety countermeasures that could reduce or mitigate those risks to pedestrians at those locations (e.g., improved signing and markings, median refuge areas)
- ☐ Prioritize those locations where these “systemic improvements” could be applied
- ☐ Fund and implement systemic pedestrian safety improvements
- ☐ Evaluate their effectiveness
- ○ NONE OF THE ABOVE that I am aware of

We would be very interested in learning more about the systemic pedestrian safety initiative you were involved with. If you checked any of the boxes above, can you please provide us with a few more details:
The scope of this initiative was (mark all that apply):

- ☐ A corridor
- ☐ A city or town
- ☐ A region or district
- ☐ A state

This systemic project was undertaken to (mark all that apply):

- ☐ Implement a particular countermeasure (e.g., median improvements, mid-block crossings).
- ☐ Implement a pedestrian safety plan or part of a “complete streets” initiative
- ☐ Identify where and how to address the highest risk of pedestrian crashes

Have the improvements been implemented?

- ○ Yes
- ○ No
- ○ Currently underway

Where you personally involved in that work?

- ○ Yes
- ○ No

Is there documentation of the project or the process that was used?

- ○ Yes (can you provide a link to that documentation in the comments section)
- ○ No

Other Systemic Safety Improvements

Has your organization implemented systemic safety improvements for any other roadway safety issues? (e.g., roadway departures)

- ○ Yes
- ○ No

Comments/Clarification
Please feel free to add any comments or clarifications that might be helpful to our study:

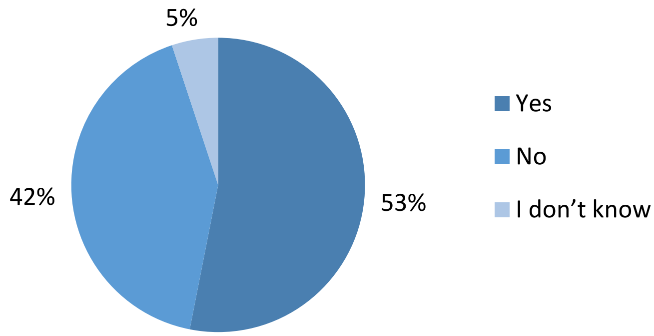
More Information
Would you be interested in learning more about systemic approaches to pedestrian safety improvements?

- ○ Yes
- ○ No, thank you.

Contact Information

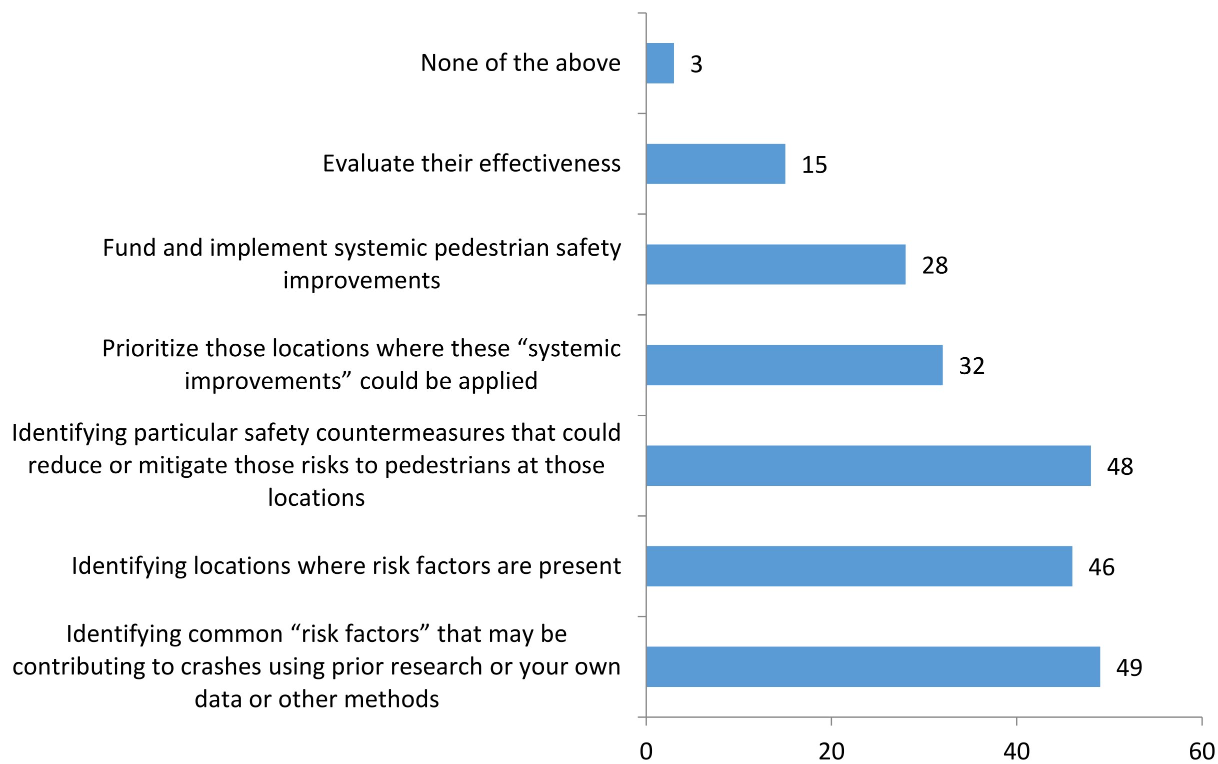
Summary of Survey Responses

Q1) My organization has experience using a systemic approach to improving pedestrian safety:



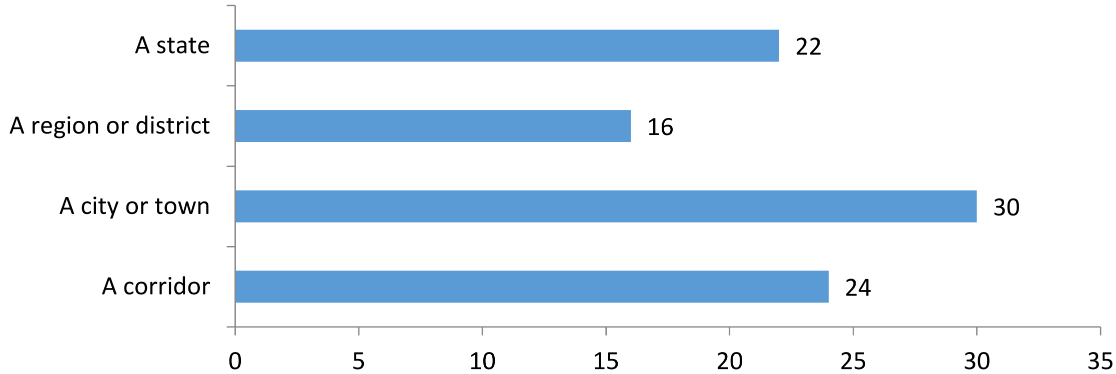
Total Respondents: 98

Q2) Has your organization undertaken any of the following activities related to their involvement with systemic pedestrian safety improvements?



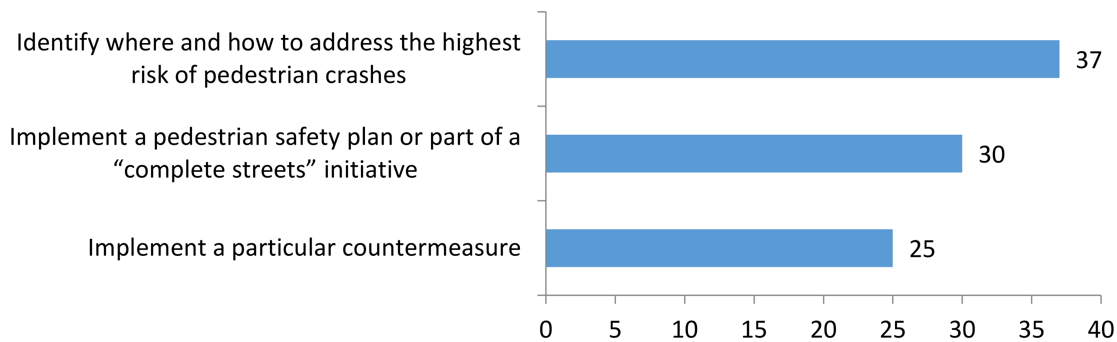
Total Respondents: 98

Q3) The scope of this initiative was:



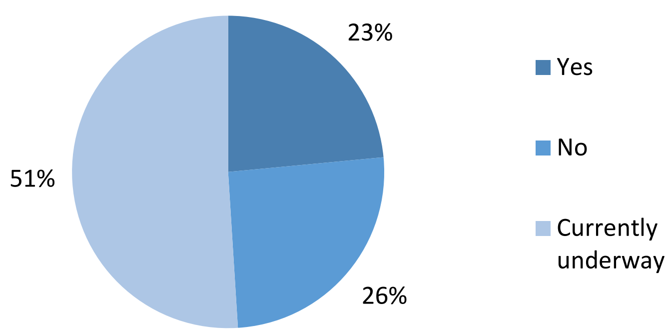
Total Respondents: 92

Q4) The systemic project was undertaken to:



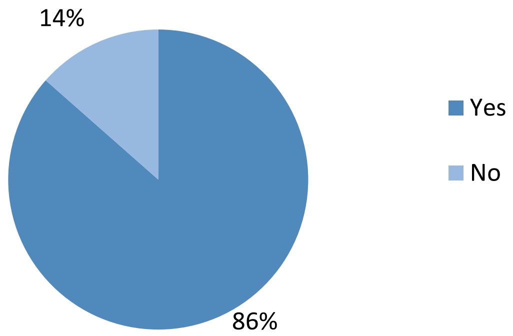
Total Respondents: 92

Q5) Have the improvements been implemented?



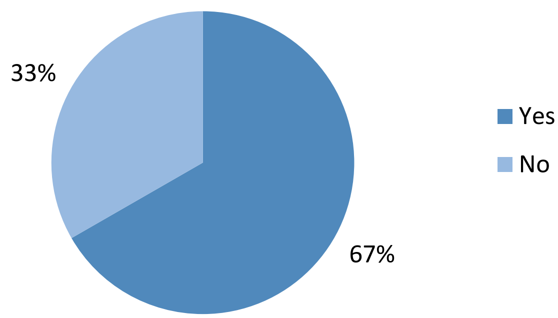
Total Respondents: 51

Q6) Were you personally involved?



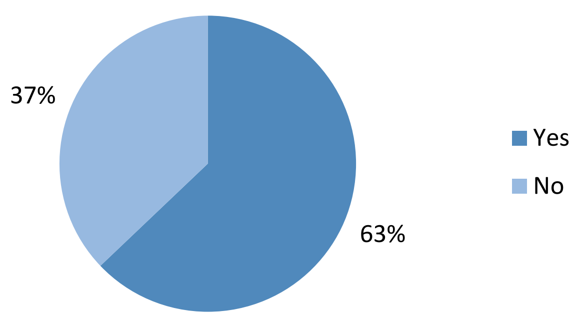
Total Respondents: 52

Q7) Is there documentation of the project or the process that was used?



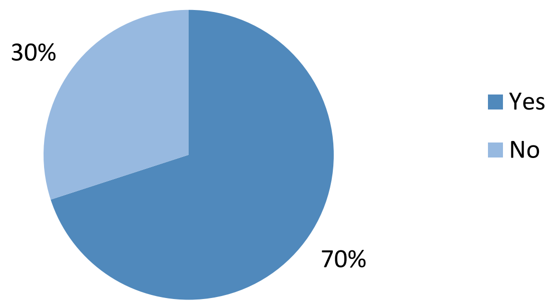
Total Respondents: 53

Q8) Has your organization implemented systemic safety improvements for any other roadway safety issues (e.g., roadway departures)?



Total Respondents: 97

Q9) Would you be interested in learning more about systemic approaches to pedestrian safety improvements?



Total Respondents: 98

APPENDIX B: Results of Prior Crash Frequency and Severity Studies Reviewed

Variables Positively Associated with Pedestrian Crash Frequencies (of the noted types) at the Location Types Indicated.

POSITIVELY Associated Variables	**Signalized 4-leg**	**Signalized 3-leg**	**Unsignalized 4-leg**	**Unsignalized 3-leg**	**All Intersections**	**All segments**	**Sources**	**Notes**
Average daily traffic volume	all, fatal & injury, injury, PDO		all, fatal & injury	all, fatal & injury, PDO	all, injury (child)	All; Mot vehicle Strt, Dark	1,2,3,4, 5,6,7, 9,11,23, 13,21,22	1. ln (sum of major and minor road ADTs); 2. ln of AADT; 3. ln of AADT; 4. AADT; 5. Log of Average annual daily motor-vehicle flows; 6. ln of AADT; 7. ln total traffic flows; 21. ln ADT (predicted) for Mot vehicle Strt; ADT/10,000 for Dark
Arterial class Major (base cat. Local)					all, motor vehicle traveling straight, pedestrian crossing at intersection		10	
Arterial class Minor (base cat. Local)					all, motor vehicle traveling straight, pedestrian crossing at intersection		10	
Arterial class Collector (base cat. Local)					all, motor vehicle traveling straight, pedestrian crossing at intersection		10	

POSITIVELY Associated Variables	Signalized 4-leg	Signalized 3-leg	Unsignalized 4-leg	Unsignalized 3-leg	All Intersections	All segments	Sources	Notes
Building volume					all, motor vehicle traveling straight, pedestrian crossing at intersection		10	
Child pedestrian activity					injury (child)	injury (child)	11	
Commercial properties					all, motor vehicle traveling straight, pedestrian crossing at intersection	Mot vehicle Strt, Dark	9,10,21	
Institutional area	all	all					8	
Land use mixed/non-residential					injury (child)		11	
Land use downtown						All, Mot vehicle Strt, Dark	13,21	
Land use suburban residential						all	13	
Land use urban					all		12	
Length of crosswalk	injury	injury					7	
Light poles/ 100 ft						Mot vehicle Strt, Dark	21	
Midblock crosswalks						Mot vehicle Strt, Dark	21	
Number of intersection legs/approaches	all						8	
Number of intersections nearby	all	all					2	

POSITIVELY Associated Variables	**Signalized 4-leg**	**Signalized 3-leg**	**Unsignalized 4-leg**	**Unsignalized 3-leg**	**All Intersections**	**All segments**	**Sources**	**Notes**
Number of lanes crossed	all	all					1	
Number of lanes on largest leg > 5					all, Motor vehicle traveling straight, pedestrian crossing at intersection		10	
Number of non-residential driveways					all		9	
Number of transit lines (through intersection)					All		23	
Number of transit stops	all	all			all, motor vehicle traveling straight, pedestrian crossing at intersection	Mot vehicle Strt, Dark	1,2,8,10,21	2. unclear data source
Pedestrian volume	all, injury	all, injury	injury	all		Mot vehicle Strt, Dark	1,2,3,5,7,8, 10,21	21. AADP +, lnAADP -
Population	all	all			all		8,10	
Population density					All	All	23	
Population under 18					all		9	
Posted speed limit						All	23	
Presence of parking					all	Mot vehicle Strt, All	10,21,23	
Presence of traffic signal					all, motor vehicle traveling straight, pedestrian crossing at intersection		10	

POSITIVELY Associated Variables	Signalized 4-leg	Signalized 3-leg	Unsignalized 4-leg	Unsignalized 3-leg	All Intersections	All segments	Sources	Notes
Ratio of Left-Turning AADT to AADT	all	all					3	
Ratio of Minor to Major AADT per day	all	all					1	
Right turn lane at adjacent intersection						Mot vehicle Strt	21	
Road length						Injury (child)	11	
Speed Limit 30, 35, 40-45, 50-60 compared to 25						Dark	21	
Total buses stopping 150"						Mot vehicle Strt, Dark	21	
Total entering vehicles	all, fatal & injury	all, fatal & injury	all, fatal & injury	all, fatal & injury	all, fatal & injury		6	
Total left turn traffic / Left-turning AADT	injury			all			7,3	
Total number of lanes	injury	injury			all	All	7,10,23	
Through lanes (4, 5+ vs. 1)						Mot vehicle Strt	21	
Total right turn traffic	injury						7	
Total through traffic	injury						7	
Two-way Left Turn Lane						Mot vehicle Strt, Dark, All	21,23	
4-legged intersection					all, motor vehicle traveling straight, pedestrian crossing at intersection		10	

POSITIVELY Associated Variables	**Signalized 4-leg**	**Signalized 3-leg**	**Unsignalized 4-leg**	**Unsignalized 3-leg**	**All Intersections**	**All segments**	**Sources**	**Notes**
5+ legged intersection					all		10	

Variables Negatively Associated with Pedestrian Crash Frequencies (of the noted types) at the Location Types Indicated.

NEGATIVELY Associated Variables	**Signalized 4-leg**	**Signalized 3-leg**	**Unsignalized 4-leg**	**Unsignalized 3-leg**	**All Intersections**	**All segments**	**Sources**	**Notes**
Average slope of terrain					all		10	
Building volume (commercial)					all, motor vehicle traveling straight, pedestrian crossing at intersection		10	
Land use single-family residential	all	all					8	
Median income	all						1	
Mean income					Motor vehicle traveling straight, pedestrian crossing at intersection	Mot vehicle Strt, Dark	10,21	
Mean speed						all, injury, PDO	13	
No intersection control					injury (child)		11	
Number of intersection legs/approaches		injury					8	
Number of schools nearby	all	all					2	
One-way						Dark	21	
Pedestrian volume at midblock (log transformed)						Mot vehicle Strt, Dark	21	
Presence of all red pedestrian phase	injury	injury					5,7	
Presence of half-red pedestrian phase	injury	injury					5,7	

NEGATIVELY Associated Variables	Signalized 4-leg	Signalized 3-leg	Unsignalized 4-leg	Unsignalized 3-leg	All Intersections	All segments	Sources	Notes
Presence of left-turn lanes	injury	injury					7	
Presence of median					all		23	
Presence of parks	all						1	
Presence of yield or stop sign					injury (child)		11	
Proportion of crosswalks					all		9	
Proportion of local streets					all, motor vehicle traveling straight, pedestrian crossing at intersection		10	

Variables with <u>Mixed Associations</u> with Pedestrian Crash Frequencies (of the noted types) at the Location Types Indicated.

MIXED Association	Signalized 4-leg	Signalized 3-leg	Unsignalized 4-leg	Unsignalized 3-leg	All Intersections	All segments	Sources	Notes
Average daily traffic volume		all, injury					1,2,3,6,7,8	1. ln (sum of major and minor road ADTs); 2. ln of AADT; 3. ln of AADT; 6. ln of AADT; 7. ln total traffic flows
Commercial properties	all	all					1,2,8; 2,8	
Pedestrian volume					all, motor vehicle traveling straight, pedestrian crossing at intersection		9,12,10	10. lnAADP positive, AADP negative

Presence of right-turn only lanes					All		9,12,23	23. Major roads positive, minor roads negative

Variables with <u>Positive</u> Associations with Pedestrian Crash Frequencies (of the noted types) in Area-Based Analyses.

POSITIVELY Associated Area-Wide Variables	**Area-wide**	**Sources**	**Notes**
Average daily traffic volume	all, pedestrian crossing, fatal & injury	16,18	
Average family size	all (child)	15	
Average volume-to-capacity ratio	all	19	
Density of businesses	all	19	
Density of hotels, motels, timeshare rooms	all	14	
Intensity of office activity	injury	20	
Intersection density (signalized)	all	14	
Number of 5-approach intersections	all	17	
Number of all-way stop intersections	all	17	
Number of bus stops	all	17	
Number of cycling commuters	all	14	
Number of road users crossing at ped crossing	all, pedestrian crossing	16	
Number of schools nearby	all, injury, possible injury	17,20	
Number of signalized intersections	all	17	
Number of subway stops	all	17	
Number of total employment	all	14	
Number of transit boardings and alightings	all	19	
Number of transit commuters in neighboring Traffic Analysis Zone (TAZ)	all	14	
Number of universities	injury	20	
Number of walking commuters	all, fatal & injury, possible injury	14,20	
Percentage of road users crossing outside the marked crossing	all, pedestrian crossing	16	
Population	all, fatal & injury	17,18,19	
Population 5-14	all (child)	15	
Population below poverty level	fatal & injury	18	
Population density	all, fatal, all (child)	14,15,20	

POSITIVELY Associated Area-Wide Variables	**Area-wide**	**Sources**	**Notes**
Population of employees	fatal & injury	18	
Presence of traffic signal	all	16	
Proportion of African American population	all	17	
Proportion of families without vehicle of neighboring TAZ	all	14	
Proportion of population high school graduates	all	17	
Proportion of Hispanic population	all, injury, possible injury	17,20	
Proportion of land use Commercial	all, injury, possible injury	17,18,20	
Proportion of land use Industrial	all, injury	17,20	
Proportion of land use Open	all	17	
Proportion of land use Residential	injury	20	
Proportion of roadway length arterial without transit	injury	18	
Proportion of roadway length five-lane	all	17	
Proportion of roadway length four-lane	all	17	
Proportion of roadway length primary without limited access	all	17	
Proportion of roadway length one-way	all	17	
Proportion of service employment in neighboring TAZ	all	14	
Proportion of uneducated population	all	17	
School enrollment K-8	all (child)	15	
School located on local road	all (child)	15	
Sidewalk length	all	14	
VMT	all	14,19	

Variables with Negative Associations with Pedestrian Crash Frequencies (of the noted types) in Area-Based Analyses.

NEGATIVELY Associated Area-Wide Variables	Area-wide	Sources	Notes
Average parents per household	all (child)	15	
Distance to nearest urban area	all	14	
Intersection density (signalized) of neighboring TAZ	all	14	
Land area (sq. miles)	fatal & injury	18	
Number of 3-approach intersections	all	17	
Population 0-14	fatal & injury	20	
Population 18+	fatal	20	
Population 5-19	fatal & injury, possible injury	20	
Population 65+	fatal & injury	18	
Proportion of bicycle lanes and trails	injury	20	
Proportion of heavy vehicle mileage in VMT	all	14	
Proportion of nonwhite households	all (child)	15	
Proportion of population with bachelor's or higher	possible injury	20	
Proportion of roadway length <30ft wide	all	17	
Proportion of roadway length local rural	all	17	
Proportion of roadway length, other thoroughfare	all	17	
Proportion of roadway length primary with limited access	all, injury	17,20	
Total park area	all	17	

Variables with Mixed Associations with Pedestrian Crash Frequencies (of the noted types) in Area-Based Analyses.

MIXED POSITIVELY AND NEGATIVELY Associated Area-Wide Variables	**Area-wide**	**Sources**	**Notes**
Median income	all (child), injury	15,20	
Number of transit commuters	all, injury	14,20	
Proportion of roadway length local	all, possible injury	14,20	

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APPENDIX C: Risk Factors with Positive or Negative Associations with Pedestrian Crash Severity by Location Types

Risk Variable	Category (if applicable)	Signalized	Unsignalized	All Intersections	Midblock	All/Non-specific Locations	Area-Wide	**Sources**
AADP (Child)					+			2
AADT		+		-		-	+ -	1,16,7
Bus involvement				-				14
Circumstance	Overcrowded footpath					+		11
	Obstructed footpath					+		11
Connectivity						-		6
Crash contributory	Distraction					+		10
	Pedestrian heedless crossing					+		11
	Pedestrian inattentive					+		11
	Others					+		11
Crash factor (primary)	Alcohol or drug (illegal) involvement					+		6
	Backing unsafely					+		6
	Failure to yield right of way					+		6
	Traffic control devices disregarded					+		6
	Unsafe speed					+		6
	View obstructed/limited					+		6
Crash location	Signalized					-		3
	Intersection					-		10
Crosswalk type	Standard		-					1
Day of the week	Weekday					+		11

Risk Variable	Category (if applicable)	Signalized	Unsignalized	All Intersections	Midblock	All/Non-specific Locations	Area-Wide	**Sources**
Direction of impact	Frontal					+		3
	Other					-		3
Driver age	Young (<25)					+		4
	Old (64+)					+		4
Driver gender	Male					+ +		4,6
Driver race/ethnicity	Black					-		4
Fault	Pedestrian	+	+					1,1
Household density				+				16
Injury location	Head injury					+		11
Intersection density	Four-leg per sq. mi.			-				16
	Three-leg per sq. mi.			+				16
Land use type	Urban					-		10
	Rural			+				5
Lighting	Dark			+				5
	Dark with no street light	+	+	+	+	+ +		1,4,6,10
	Dark with street light	+		+	+	+		1,4,6
	Dawn					+		6
	Daylight				+			4
	Daylight/dawn/dusk						-	7
Median home value							+	7
Median income						+		6
Mixed use (HHI/1000)						+		6
Number of lanes	Multiple			-		+		14,6
	Number increase			+		++		16,4
	Number increase, minor road			-				16
	One lane					+ +		6,11

Risk Variable	Category (if applicable)	Signalized	Unsignalized	All Intersections	Midblock	All/Non-specific Locations	Area-Wide	**Sources**
	Two lanes					+ +		6,11
	Right-turn (major road)			-				16
	Right-turn (minor road)			+				16
Number of pedestrians	More than 1						+	7
Park presence within 10m distance						+		6
Parking	Metered within 50 ft					-		6
Pedestrian action	At intersection					-		6
	Crossing at intersection without signal						+	7
	Crossing midblock					+		10
	Crossing with signal		+	+ + + +		- +		1,6,11,14
	Crossing with no signal or crosswalk					+		6
	Other action in roadway					+		6
	Walking along footpath					+		11
	Walking along roadway		-				-	1,7
Pedestrian age (category)	Middle/Young (~25-44)			-				5
	Middle (~40-65)		+	+		+	+	1,5,6,7
	Old (~64-79)			+		+ + + + + + +	+	5,3,4,6,10,11,13,7,15
	Very old (~75+)	+	+	+			+	1,1,5,7
	Very young (~<10)	-				+ - + +	+	1,4,10,11,13,7
	Young (~11-24)			- -		- -		5,4,10
Pedestrian age						- +	+	8,9,7
Pedestrian gender	Female			+				5
	Male					+ + +		3,4,11

Risk Variable	Category (if applicable)	Signalized	Unsignalized	All Intersections	Midblock	All/Non-specific Locations	Area-Wide	**Sources**
Pedestrian location	On the crossing					+		11
	Within 15m of the crossing					+		11
Pedestrian race/ethnicity	Black					-		4
	Hispanic					-		4
Percentage of trucks		+						1
Physical disability	Pedestrian					+		4
	Driver					+		4
Population of area	<2,500			-		+		16,4
Presence of bicycle lanes, minor road				-				16
Residential units							+	7
Retail density (per acre)						-		16
Road geometry	Straight but not level			-				14
	Flat					-		10
Road length (per 100m)					+			2
Road ownership	US-owned					+ +		4,10
	State-owned					+		4
	County-owned					+		4
Road surface condition	Dry		+					1
	Wet			+				14
Road type	City street			+ + + + +		-		6,14
	Local road					-		4
	Town					-		6
	Parking lot/other non-traffic					-		6
Road traffic flow config.	Undivided					-		4
	One-way (minor road)			+				16
	Two-way					+		11

Risk Variable	Category (if applicable)	Signalized	Unsignalized	All Intersections	Midblock	All/Non-specific Locations	Area-Wide	**Sources**
	Multi-/dual carriageway					+		11
Season	Winter (Dec-Jan-Feb)					+		6
	Autumn (Sept-Oct-Nov)					+		6
Speed limit (category)	25-50 mph (compared to < 25)					+ +		3,11
	>50 mph (compared to < 25)					+ +		3,11
Speed limit		+	+			+ +		1,4,10
Time period	Night/off peak	+						1
	Evening (6pm-12am)					+		3
	Early morning (12am-6am)					+		3
	Morning rush (7am-9:59am)					+		11
	Midday (10am-3:59pm)					+		11
	Evening (4pm-6:59pm)					+		11
Traffic aids	Poor					+		11
Traffic congestion	Severe					+		11
	Moderate					+		11
Traffic control	Presence of traffic control			-				5
	None					+ +		11,12
	Type other than signal (stop sign)					+ + +		11,12,13
Transit access						+		6
Under influence	Pedestrian			+		+ + +	+	3,4,5,7,15
	Driver					+ +		4,15
Vehicle action	Left turn before crash			+ +				14

Risk Variable	Category (if applicable)	Signalized	Unsignalized	All Intersections	Midblock	All/Non-specific Locations	Area-Wide	**Sources**
	Backing up at intersection					-		6
	Straight at intersection					+	+	6,7
	Right turn at intersection					+	-	6,7
Vehicle speed				+		- +		5,8,9
Vehicle impact speed						+ +		15,16
Vehicle type/size	Baby taxi, tempo, or tractor					+		12
	Bicycle					-		10
	Bus		+	+				1,5
	Bus or Truck					+ + + +		4,6,10,12
	Motorbike					-		10
	Pickup truck					+		3
	SUV					+		3
	Truck		+	+				1,5
	Van		+	+		+		1,5,3
Weather	Clear	-				-		1,6
	Rainy	+				- -		1,4,6
	Adverse conditions			+				5
	Cloudy					-		6
	Snow					+ -		3,6
	Fog					+		4

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