SYNTHESIS OF METHODS FOR ESTIMATING PEDESTRIAN AND BICYCLIST EXPOSURE TO RISK AT AREAWIDE LEVELS AND ON SPECIFIC TRANSPORTATION FACILITIES

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16. Abstract
This report summarizes the variety of methods used to estimate and evaluate exposure to risk in pedestrian and bicyclist safety analyses. In the literature, the most common definition of risk was a measure of the probability of a crash to occur given exposure to potential crash events. There was also consensus on a theoretical definition of exposure as a measure of the number of potential opportunities for a crash to occur. However, there is wide divergence on operational definitions of exposure, and an even wider range of exposure measures being used in practice. Geographic scale is a critical element in most exposure analyses, and most analyses reviewed could be grouped into one of four scales: 1) regional (e.g., city, county, state); 2) network (e.g., traffic analysis zone, Census tract, Census block group); 3) road segment; and, 4) point (e.g., mid-block or intersection street crossing). This report summarizes numerous examples of exposure estimation methods at these different geographic scales, and discusses the data sources and analytic methods used to estimate exposure in these different geographic scales. Other pedestrian and bicyclist risk factors besides exposure also are cataloged.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

ACS   American Community Survey
BAC   Blood Alcohol Concentration
FHWA   Federal Highway Administration
GIS   geographic information system
GPS   Global Positioning System
HCM   Highway Capacity Manual
HSIP   Highway Safety Improvement Program
ITE   Institute of Transportation Engineers
MoPeD   Model of Pedestrian Demand
MPO   metropolitan planning organization
NACTO   National Association of City Transportation Officials
NBPD   National Bicycle and Pedestrian Documentation Project
NCHRP   National Cooperative Highway Research Program
NCIPC   National Center for Injury Prevention and Control
NCSA   National Center for Statistics and Analysis
NDS   Naturalistic Driving Study
NHTS   National Household Travel Survey
NHTSA   National Highway Traffic Safety Administration
NTPP   Nonmotorized Transportation Pilot Program
ScRAM   Scalable Risk Assessment Methodology
SHRP 2   Strategic Highway Research Program 2
TAZ   traffic analysis zone
TMG   Traffic Monitoring Guide
TTI   Texas A&M Transportation Institute
TxDOT   Texas Department of Transportation
UMTRI   University of Michigan Transportation Research Institute
USDOT   United States Department of Transportation
VMT   vehicle miles of travel

ACKNOWLEDGMENTS

GLOSSARY

Term	Definition	Source
Areas	Areas consist of an interconnected set of transportation facilities serving movements within a specified geographic space, as well as movements to and from adjoining areas. The primary factor distinguishing areas from corridors is that the facilities within an area need not be parallel to each other.	2010 HCM
Areawide	Generic term that includes all geographic scales that are not facility-specific, such as neighborhood, network, system, region, city, state, etc.	Research Team
Census block	The smallest entity for which the Census Bureau collects and tabulates decennial census information; bounded on all sides by visible and nonvisible features shown on Census Bureau maps.	U.S. Census Bureau
Census block group	A combination of Census blocks that is a subdivision of a census tract.	U.S. Census Bureau
Census tract	A small, relatively permanent statistical subdivision of a county in a metropolitan area or a selected nonmetropolitan county. Census tract boundaries normally follow visible features, but may follow governmental unit boundaries and other nonvisible features in some instances; they always nest within counties. Designed to be relatively homogeneous units with respect to population characteristics, economic status, and living conditions, census tracts usually contain between 2,500 and 8,000 inhabitants.	U.S. Census Bureau
Corridors	Corridors are generally a set of parallel transportation facilities designed to move people between two locations. For example, a corridor may consist of a freeway facility and one or more parallel urban facilities.	2010 HCM
Direct demand model	A statistical model that estimates facility-specific pedestrian and bicyclist volumes based on observed volumes (at a sample of locations) and nearby context (such as land use and form, street type, etc.). Direct demand models are often based on regression analysis.	NCHRP Report 770, Research Team
Exposure	Measure of the number of potential opportunities for a crash to occur. This theoretical definition has been quantified or estimated many different ways in practice.	Research Team
Exposure scale	The most granular geographic level for which an exposure measure is desired.	Research Team
Facilities	Facilities are lengths of roadways, bicycle paths, and pedestrian walkways composed of a connected series of points and segments. The HCM defines freeway facilities, multilane highway facilities, two-lane highway facilities, urban street facilities, and pedestrian and bicycle facilities.	2010 HCM
Network	A geographic scale (mentioned in the original FHWA Statement of Work) that is most comparable to the term Area as defined in the 2010 HCM.	Research Team

Term	Definition	Source
Points	Points are places along a facility where (a) conflicting traffic streams cross, merge, or diverge; (b) a single traffic stream is regulated by a traffic control device; or (c) there is a significant change in the segment capacity (e.g., lane drop, lane addition, narrow bride, significant upgrade, start or end of a ramp influence area).	2010 HCM
Region	A geographic scale (mentioned in the original FHWA Statement of Work) that is most comparable to the term System as defined in the 2010 HCM.	Research Team
Risk	Measure of the probability of a crash to occur given exposure to potential crash events. This theoretical definition has been quantified or estimated by dividing the expected or measured number of crashes by exposure.	Research Team
Risk factor	Any attribute or characteristic that increases the likelihood of a negative safety outcome (e.g., crash or fatality).	Research Team
Segment	A segment is the length of roadway between two points. Traffic volumes and physical characteristics generally remain the same over the length of a segment, although small variations may occur (e.g., changes in traffic volumes on a segment resulting from a low-volume driveway).	2010 HCM
Sketch planning	Methods to estimate existing or future demand that are simpler alternatives to developing complex travel demand models. Often, these methods are implemented in spreadsheets or geographic information systems using existing travel survey and other data.	Research Team
System	Systems are composed of all the transportation facilities and modes within a particular region.	2010 HCM
Traffic analysis zone (TAZ)	A common areawide geography that are defined by metropolitan planning organizations for use in their travel demand forecasting models. TAZs are typically composed of multiple Census blocks.	Research Team
Travel demand model	A computerized process that estimates existing and future travel demand (often on a citywide or regional basis) given numerous inputs, such as the transportation network, population and demographic characteristics, and trip-making behavior. The end result of a travel demand model is traffic volume estimates on individual transportation network links.	Research Team
Travel survey	A systematic effort to collect information about individual travel behavior. Travel surveys are typically collected from a statistical sample of travelers for a specified day or days (not an entire month or year), and typically gather aggregate trip information (travel mode, trip purpose, trip start and end location, trip length or time, etc.).	Research Team
Work trip	Travel from home to work (also known as commuting). In their Journey to Work surveys, the U.S. Census Bureau collects trip information for only work trips. Trips that have a non-work purpose are collected by FHWA's National Household Travel Survey and other regional household travel surveys (when administered).	Research Team

EXECUTIVE SUMMARY

Background

The Federal Highway Administration (FHWA) and other federal agencies routinely work with state and local agencies to improve the safety and connectivity of bicycling and walking networks. Part of this effort has been to promote a data-driven approach to identifying and mitigating safety problems.

Pedestrian and bicyclist exposure to risk is often mentioned as a missing piece of the puzzle. The lack of readily-available pedestrian and bicyclist exposure data often make it difficult to accurately identify and then prioritize high-crash (or high-risk) locations or interpret year-to-year trends in citywide, state, or national crash statistics. Even when pedestrian or bicyclist exposure data are used, inconsistency can be present in the formulation and calculation of exposure measures between regions. Exposure has been defined based on direct counts, population, hours of travel, miles of travel, and others. Having diverse measures and definitions make direct comparisons difficult, if not impossible.

Pedestrian and bicyclist exposure is also a critical element in better understanding pedestrian and bicyclist crash causation. For example, exposure is a key variable in developing pedestrian and bicyclist safety performance functions, which are used to identify those factors that best predict when and where crashes are likely to occur. If exposure is not included, then the effects of other factors may be biased or overstated due to the omission of a key variable (exposure).

Overall Project and Task 3 Objectives

In May 2016, the FHWA's Office of Safety initiated this project to develop a standardized approach to estimate pedestrian and bicyclist exposure to risk in the form of a Scalable Risk Assessment Methodology (ScRAM). This approach will make it easier to assess pedestrian and bicyclist exposure to risk and inform project priorities and funding decisions, and will include several methods according to the scale of the needed exposure estimate. The project objectives are three-fold:
1. Synthesize and document existing technical resources.
2. Develop scalable risk assessment methods for practitioners to use to calculate pedestrian and bicyclist exposure to risk that can be applied to a facility, corridor, network/system, or regional level.
3. Widely promote the use of these risk assessment methods through outreach, training, and technical assistance.

This report documents the findings of Task 3, which sought to review and synthesize the variety of methods used to estimate and evaluate exposure in pedestrian and bicyclist safety analyses (i.e., first objective in bullet list above). Later tasks in this project will develop and promote the risk and exposure assessment methods (i.e., second and third objectives in bullet list above).

Definitions and Concepts

Chapter 2 summarizes basic definitions and concepts for risk and exposure, and then discusses these terms in the context of pedestrian and bicyclist safety analysis. It is important to define these terms and related concepts in the early stages, such that subsequent development work in this project has a clear and unambiguous foundation.

Definitions of Risk and Exposure in Transportation Safety

In the literature, most authors agree on the theoretical definition of risk as a measure of the probability of a crash to occur given exposure to potential crash events. The relationship between risk and exposure is implied in some definitions, but more explicit in others; exposure is a normalization factor (i.e., denominator) to equalize for differences in the quantity of potential crash events in different road environments. There is also general agreement in the literature on this relationship between risk and exposure:

$$Risk = \frac{Expected\ or\ measured\ crashes, by\ kind\ and\ severity}{Exposure}$$

Most theoretical definitions of exposure in the literature are similar, in that exposure is a measure of the number of potential opportunities for a crash to occur. However, there is wide divergence on operational definitions of exposure, and an even wider range of exposure measures being used in practice. For example, exposure measures in the literature have been quantified in terms of:
- Pedestrian or bicyclist volume.
- Sum of entering flows (motorized and nonmotorized) at intersection.
- Product of pedestrian or bicyclist volume (P or B) and motor vehicle volume (V), (P or B) × V.
- Square root of the above product, $\sqrt{[P\ or\ B]\ \times V}$.
- Estimated number of streets or travel lanes crossed.
- Estimated total travel distance, in person-miles of travel.
- Estimated total travel time, in person-hours of travel.
- Total number of pedestrian or bicyclist trips made (from travel survey).
- Overall census population.
- Proportion of census population who report regular walking or bicycling (from travel survey).

Several key factors may explain this wide divergence in exposure measures used:
- Scale of exposure analysis (e.g., specific street segments or areawide).
- Data availability and accuracy at application scale.
- Varying application judgment based on the above 2 factors.

Definitions of Risk and Exposure in Public Health

Much similarity exists between how risk is conceptualized and estimated between the fields of public health and transportation safety. There are many examples in the literature of epidemiological studies that use similar methods for estimating time at-risk or some other metric needed to compute risk or rates. Differences between the two fields exist for terminology such as relative risk, which needs to be considered when interpreting and comparing findings across the two fields.

Importance of Geographic Scale in Exposure Analysis

Many articles in the literature emphasize the importance of geographic scale in estimating exposure. Different data sources and methods are available or feasible at different geographic scales, and this is likely to explain some of the wide divergence in the exposure measures used in pedestrian and bicyclist safety analyses. In this report, exposure scale is defined as the geographic level for which an exposure measure is desired. The literature review indicated that most exposure analyses could be grouped into one of these four scales (see Figures ES-1 and ES-2):
1. Regional (like city, county, metropolitan statistical area, or state).

2. Network for various area definitions (like traffic analysis zone, Census tract, or Census block group).
3. Road segment (typically between major intersections or nodes).
4. Point or street crossing (intersection or mid-block).

AREAWIDE
CHAPTER 3

REGIONAL
VARIOUS GEOGRAPHIC
DEFINITIONS
- CITY
- COUNTY
- METRO. STAT. AREA
- STATE
- OTHERS

NETWORK
U.S. CENSUS GEOGRAPHIES
- BLOCK
- BLOCK GROUP
- TRACT
or
TRAFFIC ANALYSIS ZONES
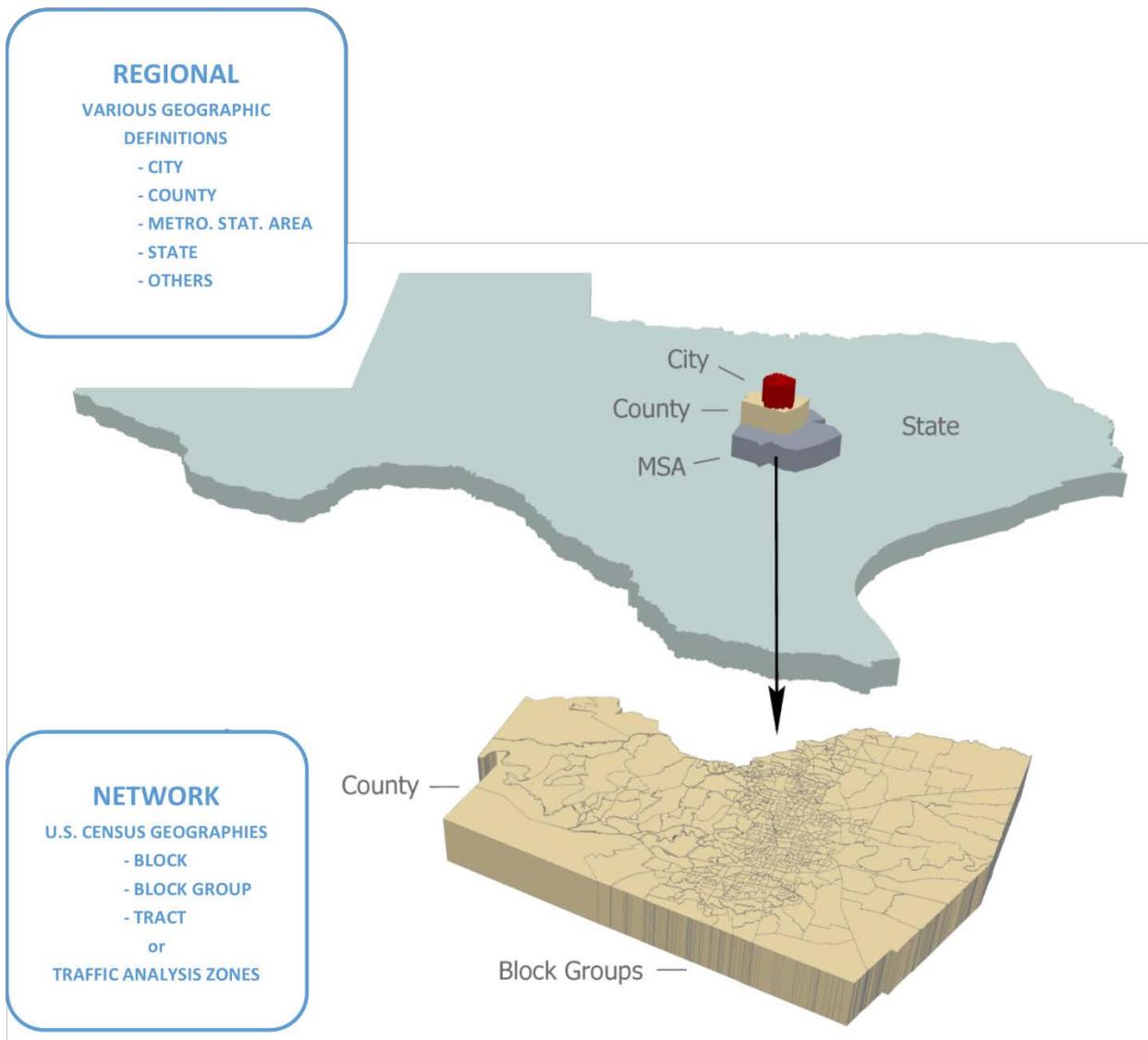
Figure ES-1. Areawide Scales (Regional and Network) in Pedestrian and Bicyclist Safety Literature

FACILITY-SPECIFIC
CHAPTER 4

POINT
INTERSECTION CROSSING

POINT
DRIVEWAY

SEGMENT

SIDEWALK

POINT
MIDBLOCK CROSSING

NOT DRAWN TO SCALE
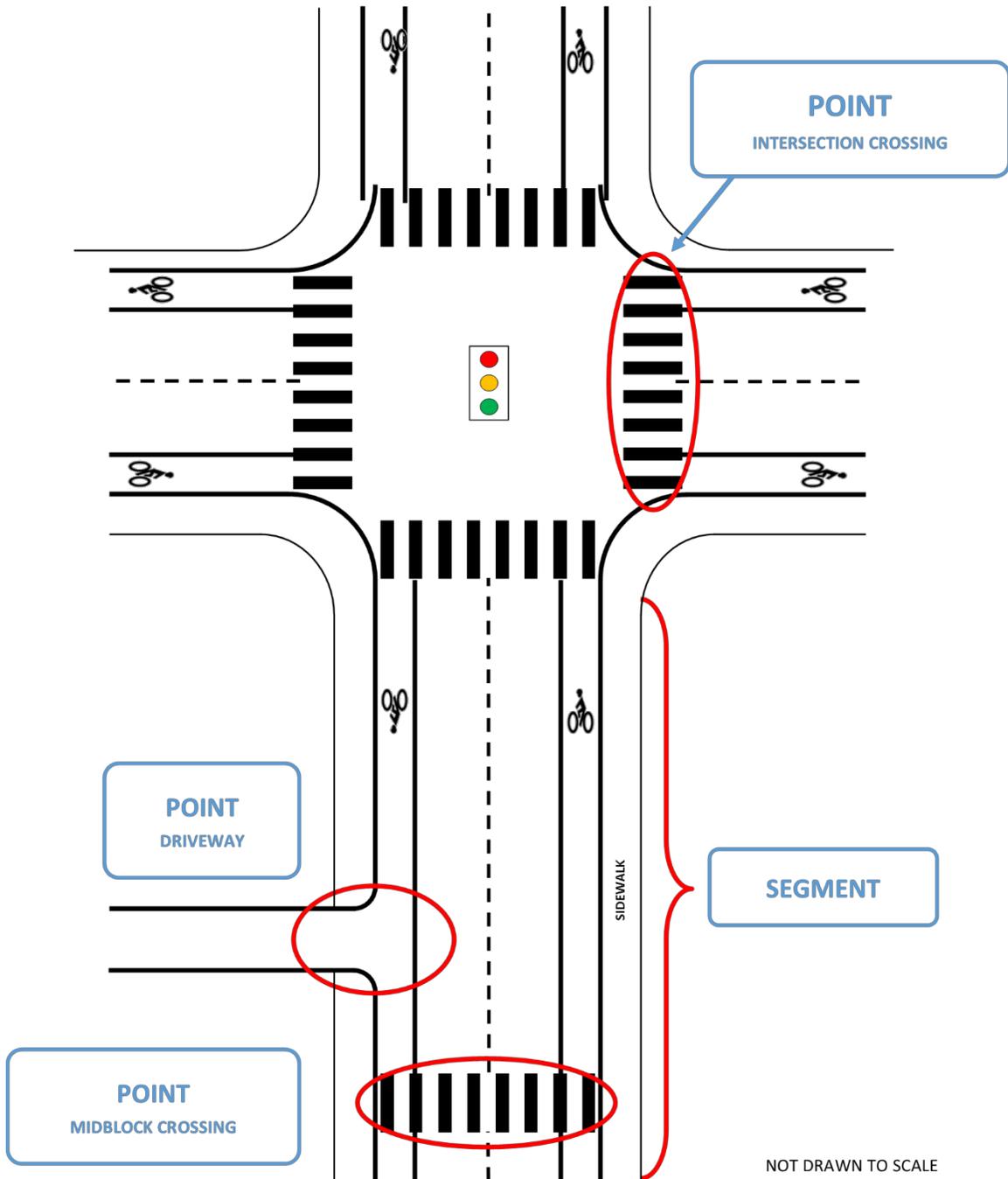
Figure ES-2. Facility-Specific Scales (Segment and Point) in Pedestrian and Bicyclist Safety Literature

Future methodological development in this project could benefit from the use of clear, unambiguous terms for various scales. For example, the Highway Capacity Manual is widely used for street and highway analysis and provides clearly-defined terms for various roadway system elements, such as points, segments, facilities, corridors, areas, and systems. Similarly, the United States Census Bureau has defined several different area geographies, including Census tracts, block groups, and blocks. Also, some metropolitan planning organizations define traffic analysis zones for use in their travel demand models. Traffic analysis zones are typically composed of multiple Census blocks, but sometimes deviate from Census geography units to accommodate local conditions.

When and Where Does Exposure Occur for Pedestrians and Bicyclists?

Most theoretical definitions of pedestrian and bicyclist exposure include references to contact with harmful vehicular traffic or opportunities for a pedestrian or bicyclist crash. For pedestrians, this occurs most explicitly during a street crossing. But several authors in the literature have posed a series of questions about when and where pedestrians or bicyclists can be considered exposed. For example, are pedestrians exposed while walking along a sidewalk that is separated from motor vehicle traffic? Are bicyclists exposed when they travel in a bike lane immediately adjacent to a motor vehicle travel lane, but then not exposed if they are riding in a separated bikeway?

In most cases, the feasibility and practicality of data collection has been used to operationalize the theoretical definition of exposure. Data cannot be collected on all pedestrian, bicyclist, and motor vehicle movements at all locations at all times. Therefore, most operational definitions of exposure have been based on pedestrian and bicyclist activity data that are already available (e.g., from travel surveys) or can be feasibly measured or estimated (e.g., from direct counts or models).

Exposure Analysis at Areawide Levels

Chapter 3 summarizes many examples of exposure analyses that were conducted at areawide levels. In this report, areawide is a generic term that includes all geographic scales that are not facility-specific. The term areawide in this chapter includes geographic scales (some not explicitly defined) such as networks, systems, regional, city, state, etc.

The areawide exposure analyses in the literature were most often performed to quantify big picture trends in pedestrian and bicyclist safety. For example (see Chapter 3 for more details):

- **FHWA Nonmotorized Transportation Pilot Program** spent $28 million in each of four pilot communities on pedestrian and bicycling infrastructure and other initiatives (e.g., outreach, marketing, education). Areawide exposure was used as a normalization factor in evaluating community-wide safety improvements in these four communities over a 10-year period.
- The **Alliance for Bicycling and Walking Benchmarking Report** publishes many performance indicators (including pedestrian and bicyclist safety) every two years in an extensive national report. The Benchmarking Report uses areawide exposure to normalize reported pedestrian and bicyclist fatalities and injuries for all 50 states and the 50 most populous cities in the U.S.

Data Sources and Methods

Most of the exposure analyses at areawide levels have used travel survey data from one or more of these sources:

- **National Household Travel Survey (NHTS):** A national survey of daily and long-distance travel that is conducted every five to seven years from a sample of U.S. households by the U.S. Department of Transportation. The survey provides estimates of trips and miles by travel mode

(including walking and bicycling), trip purpose, and other household attributes and demographics.

- **American Community Survey (ACS):** A national ongoing survey of a sample of U.S. households by the U.S. Census Bureau that gathers a wide variety of information (e.g., demographic, social, economic, housing) in addition to their primary travel mode from home to work. Therefore, the ACS does not have trip information for non-commute trips (whereas NHTS does, but on a five- to seven-year cycle). Because the ACS only asks about the primary travel mode, it does not include modes of travel that may be considered secondary (such as walk trips to public transit).
- **Regional household travel survey**: A travel survey typically conducted by a metropolitan planning organization for the purpose of developing a regional travel demand forecasting model. The frequency of these surveys varies from city to city, with some planning agencies conducting household travel surveys every eight to ten years or longer.

Most methodologies for areawide exposure analyses fall into the category of sketch planning, which is defined as methods to estimate existing or future demand that are simpler alternatives to developing complex travel demand models. Often, sketch planning methods are implemented in spreadsheets or geographic information systems using existing travel survey and other data. In some cases, the results from multiple surveys are combined to provide a more complete picture of pedestrian and bicyclist activity. In a few analyses, ACS data (which includes only primary journey-to-work trips) was combined with NHTS data (which includes all trips) to provide an accounting of all pedestrian and bicyclist trips. Also, locally collected survey data (from either regional household travel surveys or other localized data collection) has been used to supplement the federally collected ACS and NHTS data. For example, Chapter 3 summarizes an analysis for the Nonmotorized Transportation Pilot Program that uses spreadsheet-based calculations to combine ACS, NHTS, and locally collected count data to derive areawide exposure estimates. Chapter 3 contains several other similar examples whereby data from one or more travel surveys were used to develop areawide exposure estimates.

Exposure Measures

The units used in areawide exposure measures varied widely. Since the primary data source for areawide exposure analyses were travel surveys, and most travel surveys gather data on specific trips, many analyses used the number of pedestrian and/or bicyclist trips. However, some analyses focused on only journey-to-work trips (directly from ACS data), whereas other analyses included total trips (from NHTS data or combining ACS and NHTS data). In other analyses, the pedestrian and bicyclist trips were converted to pedestrian and bicyclist miles of travel using estimated trip length data. A limited number of analyses estimated pedestrian and bicyclist hours of travel using the number of trips and estimated trip times.

The geographic scale of available travel surveys is an obvious limiting factor in the scale and choice of exposure measures. The most common types of travel survey data do not have facility-specific trip information (although emerging crowdsource methods may address this in five to ten years), so exposure measures are limited to the areawide geography defined in the travel survey data that are being used. Travel surveys also do not include any data about nonmotorized traffic interactions with motorized vehicles, such that certain exposure measures (such as the product of pedestrian or bicyclist volume and motorized vehicle volume, (P or B) × V) cannot easily be estimated. These limitations notwithstanding, travel survey data can be a useful input to areawide exposure analyses when big picture exposure trends are desired for more aggregate geography and time intervals.

Exposure Analysis on Specific Transportation Facilities

Chapter 4 summarizes many examples of exposure analyses that were conducted on specific transportation facilities. In some cases, exposure estimates are calculated for specific facilities, but also aggregated to various areawide geographies.

The facility-specific exposure analyses were most often used to identify high-priority locations for pedestrian and bicyclist safety improvements and were typically conducted for an entire city. In some cases, the facility-specific information was also aggregated to provide overall trends for certain road types or for subareas within a city.

Data Sources and Methods

Most of the facility-specific exposure analyses used pedestrian and bicyclist count data from one or both of these sources:

- **Direct measurement:** Many cities are now directly collecting pedestrian and bicyclist count data on an annual basis, just like motorized vehicle counts. However, these counts are collected at a very limited number of locations, and often at the locations with the most pedestrian and bicyclist activity in the city.
- **Estimation and models:** Because directly-measured counts are typically collected at a limited number of locations, various estimation and modeling methods are often used to provide count estimates for all locations within a city or other defined area. In many cases, the sample of direct counts is used in the development and calibration of these estimation models.

For direct measurement of pedestrian and bicyclist counts, much progress has been made in the past ten years. Several companies now offer automated count equipment that helps to make pedestrian and bicyclist counting more efficient and cost-effective. The National Bicycle and Pedestrian Documentation Project provided early guidance and helped to promote count data collection. Since then, FHWA has included a chapter specifically devoted to nonmotorized traffic monitoring in their 2013 edition of the Traffic Monitoring Guide. In 2014, NCHRP Report 797: Guidebook on Pedestrian and Bicycle Volume Data Collection was published and is a comprehensive resource on pedestrian and bicycle count data collection. This direct measurement approach (calculating exposure from systematic traffic monitoring programs) is the current state-of-the-practice for motor vehicle exposure estimation.

For estimating pedestrian and bicyclist counts, direct demand models have been the most widely used models for facility-specific exposure estimation thus far, and typically use regression analysis to relate directly measured counts to other measured attributes of the adjacent environment (e.g., land use and form, street type, etc.). Assuming that these measured attributes are available citywide, the regression model allows one to extend the sample of facility-specific counts to all facilities citywide. Chapter 4 provides details on other types of modeling approaches that have been used on a limited basis or could be used for facility-specific exposure estimation. These approaches include regional travel demand models, geographic information system (GIS)-based models, trip generation and flow models, network analysis models, discrete choice models, and simulation-based traffic models.

Exposure Measures

Similar to the areawide exposure analyses, the units used in facility-specific exposure measures varied widely. Since the primary data source was pedestrian and bicyclist count data (rather than surveyed trip data in areawide exposure analyses), the units of exposure typically were a volume count for specified time period or a distance traveled (calculated by multiplying a count by a street crossing width or road

segment length). In a few cases where the exposure values were very high, the exposure was given in units of 1 million or 10 million (e.g., 1 million pedestrian miles traveled, 10 million pedestrian crossings).

Unlike areawide exposure analyses, several of the facility-specific exposure analyses did account for the interaction of nonmotorized and motorized traffic in their exposure measure. Several analyses computed the product of pedestrian or bicyclist traffic and motorized traffic ((P or B) × V) at intersections or other street crossings. A few other analyses used exposure measures such as pedestrian crossings (or pedestrian miles) per entering motorized vehicle. Thus, having more granular exposure data on specific facilities does provide a better opportunity to quantify the level of interaction between pedestrian or bicyclist traffic and motorized vehicle traffic.

Risk Factors Other than Exposure

Chapter 5 summarizes many risk factors (other than exposure) for pedestrian and bicyclist safety. Findings from most of these studies indicate association, not causation, between potential risk factors and crash outcomes. The risk factors were categorized into two basic groups:
1. **Disaggregate risk factors** are facility-specific (e.g., facility quality or condition) or individual-specific attributes (e.g., age, socioeconomic, behavioral).
2. **Aggregate risk factors** are associated with areawide geography (e.g., land use, urban form).

For disaggregate risk factors, many studies have shown that poor facility conditions (e.g., no or inadequately designed pedestrian and bicyclist infrastructure) are a significant risk factor, as well as facilities where high-speed, high-volume motorized traffic routinely interacts with pedestrian and bicyclist traffic. Significant risk factors for individuals are age (i.e., children and seniors), intoxication, nighttime visibility, and distracted behavior.

For aggregate risk factors, many studies have documented the effects of land use (in particular, population density) on pedestrian and bicyclist safety. Several studies have also found that neighborhoods with lower-income and minority communities have a higher risk for pedestrian and bicyclist crashes.

Conclusions

The project team reviewed and synthesized over 280 research and technical documents (see Bibliography) on pedestrian and bicyclist risk and exposure and developed these key conclusions:
- **Geographic scale is a key parameter in exposure analyses:** Detailed exposure data cannot be collected on all pedestrian, bicyclist, and motor vehicle movements at all locations at all times. Therefore, the scale(s) for which exposure is required will determine what data source and methods are practical and feasible. Future methodological development in this project could benefit from the use of clear, unambiguous terms for various scales. To encourage widespread consistency and adoption by practitioners, existing terms and definitions should be drawn from widely used manuals, guidebooks, or references. The U.S. Census provides standardized terms and definitions for several different areawide geography scales. Similarly, the Highway Capacity Manual provides terms and definitions for various scales of roadway system elements.

- **Areawide exposure measures are inconsistent despite similar travel survey data:** The units used in areawide exposure measures varied widely, despite many analyses using the same two

national travel surveys (i.e., ACS and NHTS) as their base data source. If areawide exposure measures use the same base travel survey data, one might expect an emerging consensus on the best approach for using the same or similar trip data to calculate areawide exposure measures. The number of pedestrian and bicyclist trips was a common exposure measure, but even with this measure, some analyses reported only on work trips whereas some reported on all trips. Even if consensus on a single areawide exposure measure cannot be achieved, future methodological development in this project should focus on identifying a few good measures that are designated as a best practice for estimating areawide exposure.

- **Facility-specific exposure analyses often use counts in combination with models:** One of the most common approaches to estimate facility-specific exposure has been to combine pedestrian and bicyclist counts with estimation models, such that exposure can be estimated for all facilities within a defined geographic area (typically citywide). Given the wide variety of estimation models in use, it may be difficult to single out a single best practice for future methodological development in this project. This project could focus on providing additional guidance on the most common estimation model (i.e., direct demand model), while still acknowledging and providing high-level details on other estimation model approaches.

  Similar to areawide exposure measures, the units used in facility-specific exposure measures varied widely. This is also despite the fact that direct measurement and estimation models both produce the same basic data item: counts of pedestrians and/or bicyclists at a point or along a street segment for a defined time interval. As with areawide exposure measures, it may be difficult to achieve consensus on a single facility-specific exposure measure. However, there would be value in defining a few good measures that are designated as a best practice for estimating facility-specific exposure.

Next Steps

Based on the findings and conclusions in this Task 3 report, the TTI-led project team will develop a conceptual framework and design for risk exposure estimation at several different geographic scales (Task 4.A. of this project). The conceptual framework will be based on best practices as identified in this report, as well as other practices and processes that may be in development (such as those from NCHRP 17-73, Systemic Pedestrian Safety Analyses). The first draft of the conceptual framework will be available for review in May 2017.

CHAPTER 1. INTRODUCTION

Background

The U.S. Department of Transportation (USDOT) has designated improved pedestrian and bicyclist safety as a top priority. The Federal Highway Administration (FHWA) and other federal agencies routinely work with state and local agencies to provide technical resources, develop analytical approaches, and highlight best practices to improve the safety and connectivity of bicycling and walking networks. Part of this effort has been to promote a data-driven approach to identifying and mitigating safety problems. Various data sets and analytic approaches have been developed to improve the quality and analysis of pedestrian and bicyclist crash data.

Pedestrian and bicyclist exposure to risk is often mentioned as a missing piece of the puzzle. The lack of readily-available pedestrian and bicyclist exposure data often make it difficult to accurately identify and then prioritize high-crash (or high-risk) locations or interpret year-to-year trends in citywide, state, or national crash statistics. Even when pedestrian or bicyclist exposure data are used, inconsistency can be present in the formulation and calculation of exposure measures between regions. Exposure has been defined based on direct counts, population, hours of travel, miles of travel, and others. Having different exposure measures and definitions make direct comparisons difficult, if not impossible. If pedestrian and bicyclist safety analyses were to use a consistent exposure measure (such as the number of street crossings or the number of pedestrian or bicyclist trips), then direct comparisons among studies and analyses would be much easier and meaningful.

Pedestrian and bicyclist exposure is also a critical element in better understanding pedestrian and bicyclist crash causation. For example, exposure is a key variable in developing pedestrian and bicyclist safety performance functions, which are used to identify those factors that best predict when and where crashes are likely to occur. If exposure is not included, then the effects of other factors may be biased or overstated due to the omission of a key variable (exposure).

In early 2016, FWHA published the Final Rule on the Highway Safety Improvement Program (HSIP) and Safety Performance Management Measures (http://safety.fhwa.dot.gov/hsip/spm/). The Final Rule does require that state DOTs and metropolitan planning organizations (MPOs) report five safety management performance measures, one of which is the *number of non-motorized fatalities and non-motorized serious injuries*. Since two of the motorized safety performance measures include exposure (i.e., 100 million vehicle miles traveled), there was consideration about whether to include exposure in the non-motorized measure. However, several comments on the Draft Rule expressed concern about the lack of suitable non-motorized exposure data, and therefore the Final Rule does not include exposure in the non-motorized safety performance measure.

Overall Project Objectives

In May 2016, the FHWA's Office of Safety initiated this project to develop a standardized approach to estimate pedestrian and bicyclist exposure to risk in the form of a Scalable Risk Assessment Methodology (ScRAM). This approach will make it easier to assess pedestrian and bicyclist exposure to risk and inform project priorities and funding decisions, and will include several methods according to the scale of the needed exposure estimate. The project objectives are three-fold:

1. Synthesize and document existing resources that agencies can use to assess pedestrian and bicyclist exposure to risk.
2. Develop scalable risk assessment methods for practitioners to use to calculate pedestrian and bicyclist exposure to risk that can be applied to a facility, corridor, network/system, or regional level. The risk assessment methods are likely to include separate but parallel modules for estimating pedestrian and bicyclist exposure.
3. Widely promote the use of these risk assessment methods through outreach, training, and technical assistance.

Task 3 Objectives

This report documents the findings of Task 3, which sought to review and synthesize the variety of methods used to estimate and evaluate exposure in pedestrian and bicyclist safety analyses (i.e., first objective in bullet list above). Later tasks in this project will develop and promote the risk and exposure assessment methods (i.e., second and third objectives in bullet list above). This report differentiates between exposure on a network or regional basis and exposure on specific transportation facilities (e.g., a street crossing or mid-block link).

Report Overview

This report includes the following chapters:
- **Chapter 1. Introduction**: Summarizes the need for risk exposure measures and outlines the overall project objectives and the specific objective of Task 3.

- **Chapter 2. Definitions and Concepts**: Outlines basic definitions and concepts for risk and exposure, and then discusses these terms in the context of pedestrian and bicyclist safety analysis.

- **Chapter 3. Exposure Analysis at Areawide Levels**: Summarizes the use of exposure measures at areawide levels, and describes the data sources and methods that could be used for exposure measures at these more aggregate analysis levels.

- **Chapter 4. Exposure Analysis on Specific Transportation Facilities**: Summarizes the use of exposure measures on specific transportation facilities (e.g., street crossings, street segments) and describes the data sources and methods that could be used for exposure measures at these more granular analysis levels.

- **Chapter 5. Risk Factors Other Than Exposure**: Outlines the variety of risk factors (other than exposure) that affect pedestrian and bicyclist safety.

- **Chapter 6. Conclusions**: Develops and summarizes conclusions based on the findings of the synthesis of practice and literature review.

CHAPTER 2. DEFINITIONS AND CONCEPTS

This chapter summarizes basic definitions and concepts for risk and exposure, and then discusses these terms in the context of pedestrian and bicyclist safety analysis. It is important to define these terms and related concepts in the early stages, such that subsequent development work in this project has a clear and unambiguous foundation.

The following discussion draws from key research articles and papers written about risk and exposure in the past 40 years. The published literature on risk and exposure is vast and extensive, as Hauer indicates in his discussion to a published article (Molino 2009):

> "The number of papers and books written about the concept of exposure can fill a large bookcase. It is an elusive and controversial concept."

Defining Risk

In the literature, risk and exposure are fundamentally related but have specific individual meanings. Also, several authors provide theoretical definitions of risk or exposure that are challenging to put into practice. In some cases, these or other authors have provided an operational or working definition to complement the theoretical definition. The following discussion will differentiate between theoretical and operational definitions.

Most authors agree on the theoretical definition of risk as a measure of the probability of a crash to occur given exposure to potential crash events. Specifically, risk has been defined as:

- "…conditional probability that an accident occurs given the opportunity for one." (Chapman 1973)

- "…a measure of the probability of a potential accident event resulting in an accident." (Cameron 1979)

- "… the probability (chance) of accident occurrences in a trial", where a trial corresponds to a unit of exposure, such as a defined time spent walking or a defined number of street crossings. (Hauer 1982)

- "…probability of an accident happening in a particular road environment." (Bly et al. 1999)

- "…the probability that a pedestrian-vehicle collision will occur, based on the rate of exposure." (Raford and Ragland 2004)

- "Probability of collision/injury/fatality per unit of exposure." (Greene-Roesel et al. 2007)

Relationship of Risk to Exposure

The relationship between risk and exposure is implied in some definitions, but more explicit in others; exposure is a normalization factor (i.e., denominator) to equalize for differences in the quantity of potential crash events in different road environments. There is general agreement in the literature on

this relationship between risk and exposure. For example, consider the following (most of which are operational definitions of risk):

- $Risk = \frac{Pedestrian\ accidents}{Pedestrian\ accident\ exposure}$ (Cameron 1982)

- $Risk = \frac{Expected\ number\ of\ accidents\ by\ severity}{Exposure}$ (Hauer 1982)

- $Risk = \frac{Number\ of\ casualties}{Exposure}$ (Keall 1995)

- $Risk = \frac{Crashes}{Exposure}$ (Molino et al. 2009)

Defining Exposure

In the literature, most theoretical definitions of exposure are similar, in that exposure is a measure of the number of potential opportunities for a crash to occur. Specifically, exposure has been defined as:

- "…number of opportunities for accidents of a certain type in a given time in a given area..." (Chapman 1973)

- "…number of potential accident events, i.e., an event involving a pedestrian and a vehicle which is a pre-condition of a collision between them, but does not necessarily result in such." (Cameron 1982)

- "…a [probabilistic] trial… the results of such a trial is the occurrence or non-occurrence of an accident (by type, severity, etc.)." (Hauer 1982)

- "…being in a situation which has some risk of involvement in a road traffic accident, a risk which theoretically can be measured for both active and passive elements of the traffic system." (Wolfe 1982)

- "…a condition which must be present in order to have an accident." (Tobey et al. 1983)

- "…measure of the opportunity for accidents to occur…" (Bly 1999)

- "…rate of contact with potentially harmful vehicular traffic." (Raford and Ragland 2004)

- "Contact or amount of contact with potentially harmful situation." (Greene-Roesel et al. 2007)

Despite the consensus on a theoretical exposure definition, there is wide divergence on operational definitions of exposure, and an even wider range of exposure measures being used in practice. For example, exposure measures in the literature have been quantified in terms of:

- Pedestrian or bicyclist volume.
- Sum of entering flows (motorized and nonmotorized) at intersection.
- Product of pedestrian or bicyclist volume (P or B) and motor vehicle volume (V), (P or B) × V.
- Square root of the above product, $\sqrt{(P\ or\ B)\ \times V}$.
- Estimated number of streets or travel lanes crossed.
- Estimated total travel distance, in person-miles of travel.

- Estimated total travel time, in person-hours of travel.
- Total number of pedestrian or bicyclist trips made (from travel survey).
- Overall census population.
- Proportion of census population who report regular walking or bicycling (from travel survey).

Chapters 3 and 4 provide more detail on the use of these various exposure measures. All of these exposure measures were intended to represent the same theoretical construct of pedestrian or bicyclist contact with potentially harmful traffic situations (i.e., exposure). However, several key factors are likely to explain the wide divergence in exposure measures used:

- **Exposure scale:** For example, is an exposure measure sought for individual intersection crossings and/or road segments? Or for aggregate zones or user groups in an entire city?

- **Data availability and accuracy at application scale:** For example, what data could be feasibly gathered at that application scale for a jurisdiction, and how accurate are those data?

- **Varying application judgment:** For example, there are differing opinions on the best approach to operationalize the theoretical definition of exposure for different applications.

Public Health and Epidemiological Approaches to Estimate Exposure

Within the broad field of public health, quantifying the risk of injury or other health condition or disease is a focus of the discipline of epidemiology. The goal is to compare the risk in exposed groups to unexposed groups in order to identify risk factors or factors that cause a health condition such as injury. Ideally, the identified risk factors are then targeted for intervention in order to prevent injury or lessen its negative impact on health and well-being. Epidemiologists define *risk* as the "probability of an event during a specified period of time" (Rothman, Greenland, and Lash 2008). This is similar to the theoretical definitions provided by Hauer (1982) and others earlier in this chapter.

For how risk is computed, the basic equation is similar when comparing applications in transportation safety versus epidemiology. However, the terminology differs in how the denominator is described and how the term exposure is used. In addition, epidemiologists place an emphasis on defining the population and the time period for estimates of risk. Ideally, the estimates of risk can be generalized to a population larger than the sample upon which the estimate is based. Two common measures of risk in epidemiology are frequently referred to as cumulative incidence and incidence density. These are computed as follows:

- $Cumulative\ Incidence = \frac{Number\ of\ events\ (e.g., injured\ people)}{Number\ of\ people\ at-risk}$ (Gordis 2014)

- $Incidence\ Density = \frac{Number\ of\ events\ (e.g., injured\ people)}{Amount\ of\ time\ at-risk}$ (Gordis 2014)

The key difference between these two measures is the denominator. In the first, the denominator is number of people at-risk of developing the injury or other health outcome. In the second, the denominator is the amount of time at-risk which is often expressed in terms of person-years, person-hours, or person-days, as examples. Epidemiological studies that focus on transportation populations often use vehicle miles of travel (VMT) as the denominator for person-time at-risk of sustaining an injury or being involved in a crash. Since these measures of risk focus on the frequency of events such as injury

during a specified time period, they are often referred to as rates. This is especially true when the denominator is based on the amount of person-time at-risk (i.e., incidence density) rather than simply the number of people at-risk (i.e., cumulative incidence).

Although different terminology may be used, these equations and the conceptual underpinning behind them are very similar to those presented earlier in this chapter for pedestrian and bicyclist safety. The main difference is how the denominators are described and how the term exposure is used. In pedestrian and bicyclist safety, exposure tends to refer to the denominator, which is quantified in many ways including person-hours of travel or person-miles of travel. In epidemiology, the term exposure tends to be used within the context of identifying specific factors that cause or contribute to injury or some other health outcome. Examples include lack of restraint use or helmet use and its role in the occurrence of fatal injury. As described above, the denominator refers to the people at-risk or amount of time at-risk.

The basic method for determining whether or not an exposure is associated with injury is to compare the risk of injury in the exposed versus the unexposed group. As an example, a study of the efficacy of bicycle helmets could involve comparing the risk of death due to brain injury among bicyclists not wearing a helmet to the risk of death due to brain injury among bicyclists wearing a helmet. This comparison is accomplished by computing a measure known as relative risk. Relative risk that is computed based on cumulative incidence is called a risk ratio whereas relative risk computed based on incidence density is called a rate ratio. The basic equations are below:

- $Risk\ ratio = \frac{Risk\ in\ exposed}{Risk\ in\ unexposed}$ (Gordis 2014)

- $Rate\ ratio = \frac{Rate\ in\ exposed}{Rate\ in\ unexposed}$ (Gordis 2014)

Their interpretation is similar. A relative risk value equal to 1.0 is indicative that the exposure did not contribute to injury or other outcome. A relative risk value greater than 1.0 is interpreted as the exposure increasing the risk of sustaining an injury. A relative risk value less than 1.0 is indicative that the exposure decreases the risk of sustaining an injury. Although this is the more typical use of the term exposure in epidemiology, the term also is used when referring to person-time at-risk of sustaining an injury. This could be expanded to include person-distance traveled or other similar metrics. In this context, it could be used as the amount of time exposed to a potential hazard such as the roadway. This use is in line with the definitions provided earlier in this chapter. While the computations provided here illustrate the basic concepts of risk and exposure in epidemiology, a wide array of statistical methods are used in epidemiology. These range from simplistic computations such as those illustrated above to complex modeling.

In the published literature, there is much overlap between risk and exposure studies in the fields of traffic safety and epidemiology. Greene-Roesel et al. (2007) provide definitions and descriptions for pedestrian exposure that are nearly identical to textbooks in epidemiology. This includes the elements of risk discussed above along with in-depth discussions of target populations and methods for sampling larger populations. This is beneficial so that inferences can be drawn from a sample to a larger population, which is often more cost-effective and efficient. There are many other examples of individual epidemiological studies of pedestrian and bicycle safety where risk and relative risk are estimated based on quantified exposure. Recent examples include a study from North Carolina wherein pedestrian and bicycle crash-related injury rates were computed (Kerr et al. 2013). For risk or rate estimates, the numerator was nonfatal and fatal injury while the denominator was the number of trips

at-risk. In this study exposure or time at-risk was estimated using methods from traffic safety (Durham Comprehensive Bicycle Transportation Plan 2006). DiMaggio et al. (2015), in their evaluation of the Safe Routes to School program in Texas, estimated the risk of pedestrian and bicyclist injury in school-age children. They used population for the denominator in their estimates of risk over time. Both of these studies used more complex statistical modelling to compute relative risk measures or assess program impact. In addition, others have used more complex methods for estimating crash and injury risk such as decomposition methods (Dellinger et al. 2001). These were implemented in a recent Spanish study of pedestrian traffic-related fatalities (Onieva-Garcia et al. 2016).

Some reports may use the same terminology, but use markedly different equations to calculate measures such as relative risk. For example, Raford and Ragland (2004) present an equation for relative risk that, in an epidemiological context, fits better with the definition of a risk or rate. A similar discrepancy can be found in the report by Bly et al. (1999) in their comparison of child pedestrian safety in three European countries. To contrast, the United States Road Assessment Program (Harwood et al. 2010) employs equations for relative risk that are more in line with traditional epidemiological computations.

In summary, there is much similarity in how risk is conceptualized and estimated between the fields of public health and transportation safety. There are many examples in the literature of epidemiological studies that use similar methods for estimating time at-risk or some other metric needed to compute risk or rates. Differences between the two fields exist in terminology such as relative risk, and these differences need to be considered when interpreting and comparing findings across the two fields.

Importance of Geographic Scale in Exposure Analysis

Many articles in the literature emphasize the importance of scale in estimating exposure. Similarly, scale has already been mentioned several times in this chapter when discussing how the theoretical definition of exposure can be operationalized in a practical way. In this report, exposure scale is defined as the most granular geographic level for which an exposure measure is desired. For example, is an exposure measure sought for a selected number of individual street crossings? Is an exposure measure sought for certain roadway segments? Or is an exposure measure sought for a defined areawide geography, such as traffic analysis zones (TAZs), Census tracts, or Census block groups?

There is a need to differentiate between scale and coverage when discussing exposure estimation:
- **Scale** is the **geographic level** of the desired exposure estimation.
- **Coverage** denotes the **total geographic area** that is included in an exposure analysis.

For example, consider an exposure estimation approach that uses a travel demand forecasting model to estimate segment-based pedestrian and bicyclist volumes and exposure for the entire region. In this example, the scale is at a segment level, since that is the most granular geographic level for travel demand models. The coverage of the travel demand model is for the entire region.

The original statement of work for this project referenced four different scale levels:
1. Facility.
2. Corridor.
3. Network/system.
4. Regional.

The literature review indicated that most exposure analyses were more closely aligned to these four scales:
1. Street crossing (intersection or mid-block).
2. Road segment (typically between major intersections or nodes).
3. Network for various area definitions (such as a TAZ, Census tract, or Census block group).
4. Regional (such as city, county, metropolitan statistical area, or state).

Chapters 3 and 4 provide additional details on the scale and coverage of exposure analyses that were documented in this literature review.

Future methodological development in this project could benefit from the use of clear, unambiguous terms for various scales. In particular, the 2010 Highway Capacity Manual (HCM) is widely used for street and highway analysis and provides clearly-defined terms for various roadway system elements, such as points, segments, facilities, corridors, areas, and systems. Figure 1 shows HCM roadway system elements to provide context and their relative scales to one another. These HCM roadway elements were chosen as scale classifications in Chapter 4 since they are widely accepted and are easily understandable to practitioners attempting to conduct an exposure assessment.

For the network/system and regional scales, standardized terms and definitions do exist for areawide geography. The U.S. Census Bureau has defined several different area geographies, including Census tracts, block groups, and blocks (Figure 2). These area geographies are regularly used in collecting and reporting travel survey data (e.g., the number of pedestrian and bicyclist trips) have been used in many areawide exposure analyses (see Chapter 3).

TAZs are another common areawide geography that are defined by metropolitan planning organizations (MPOs) for use in their travel demand forecasting models (see polygons with blue outlines in Figure 3). TAZs are typically composed of multiple Census blocks, since the demographic information in travel demand models is typically populated by aggregating Census data. However, there are cases where a TAZ definition may deviate from Census geography units to accommodate local conditions.

To provide a visual comparison example of TAZs to Census geography, Figure 3 also shows Census block groups (see polygons with red outline). In Figure 3, the following can be seen from this comparison example: 1) although individual zone sizes vary, TAZs are somewhat comparable in size to Census block groups; and 2) TAZ boundaries can deviate from Census geography boundaries when necessary to better account for traffic conditions.
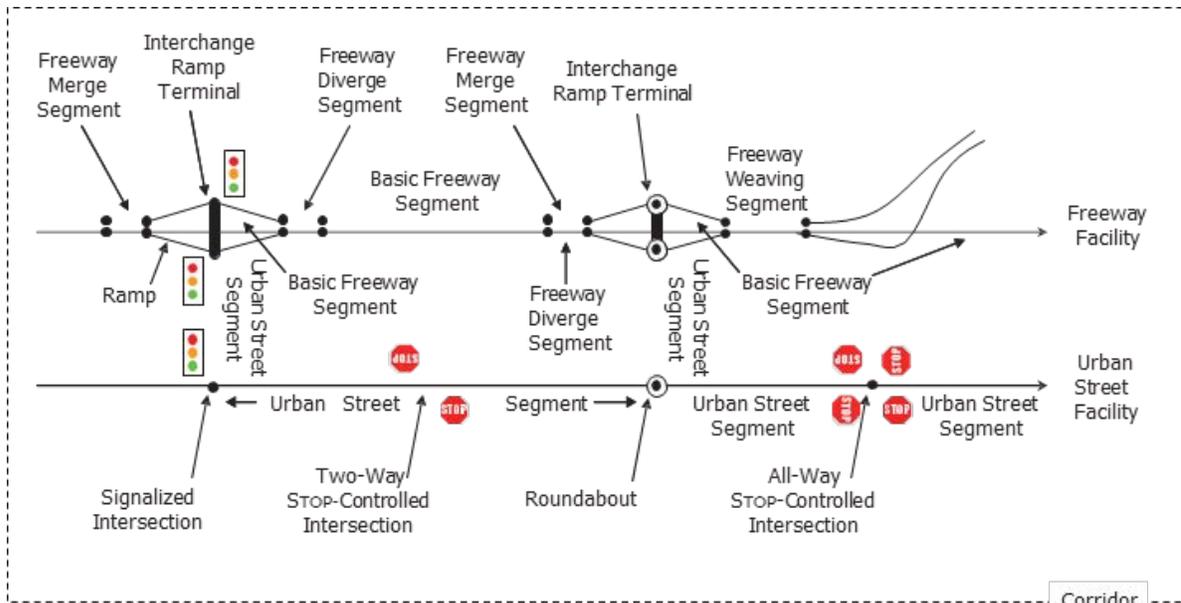
Points, Segments, Facilities, and Corridors
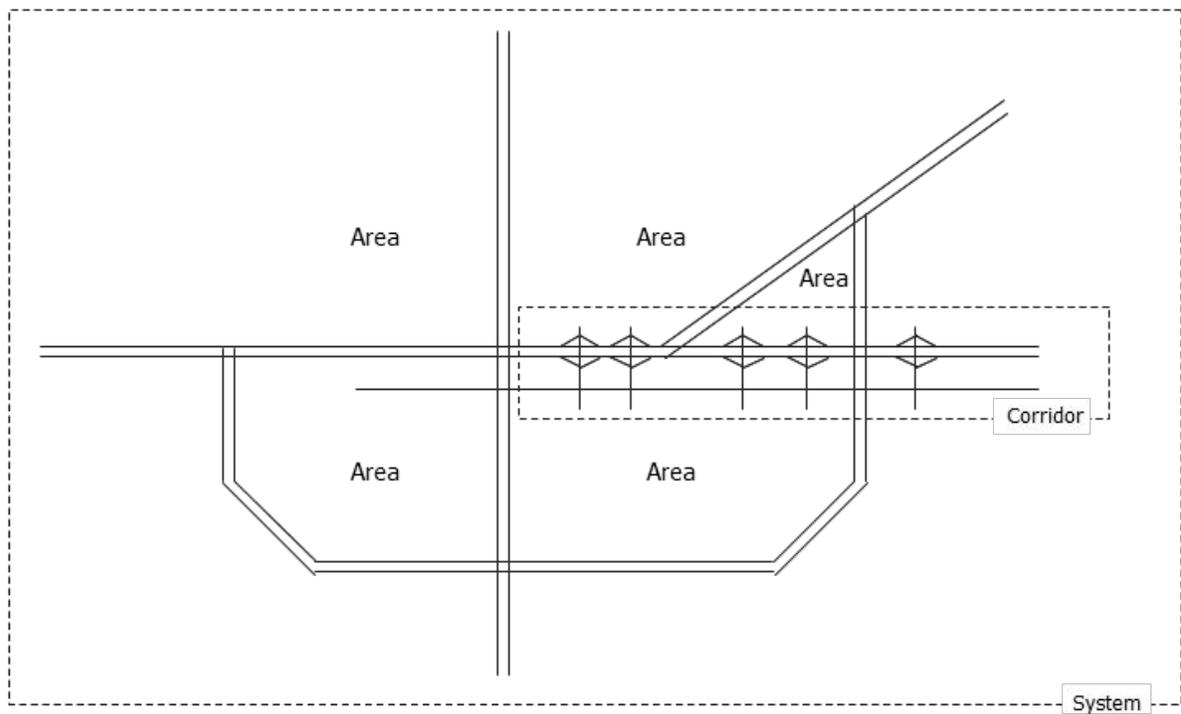
Corridors, Areas, and Systems

(Source: 2010 HCM Volume I, Exhibit 2-1)

Figure 1. HCM Standard Definitions of Roadway System Elements (Scale)

United States Census Geography

State in the nation

County in the state

Tract in the county

Block group in the tract

Block in the block group

Block centroid in the block
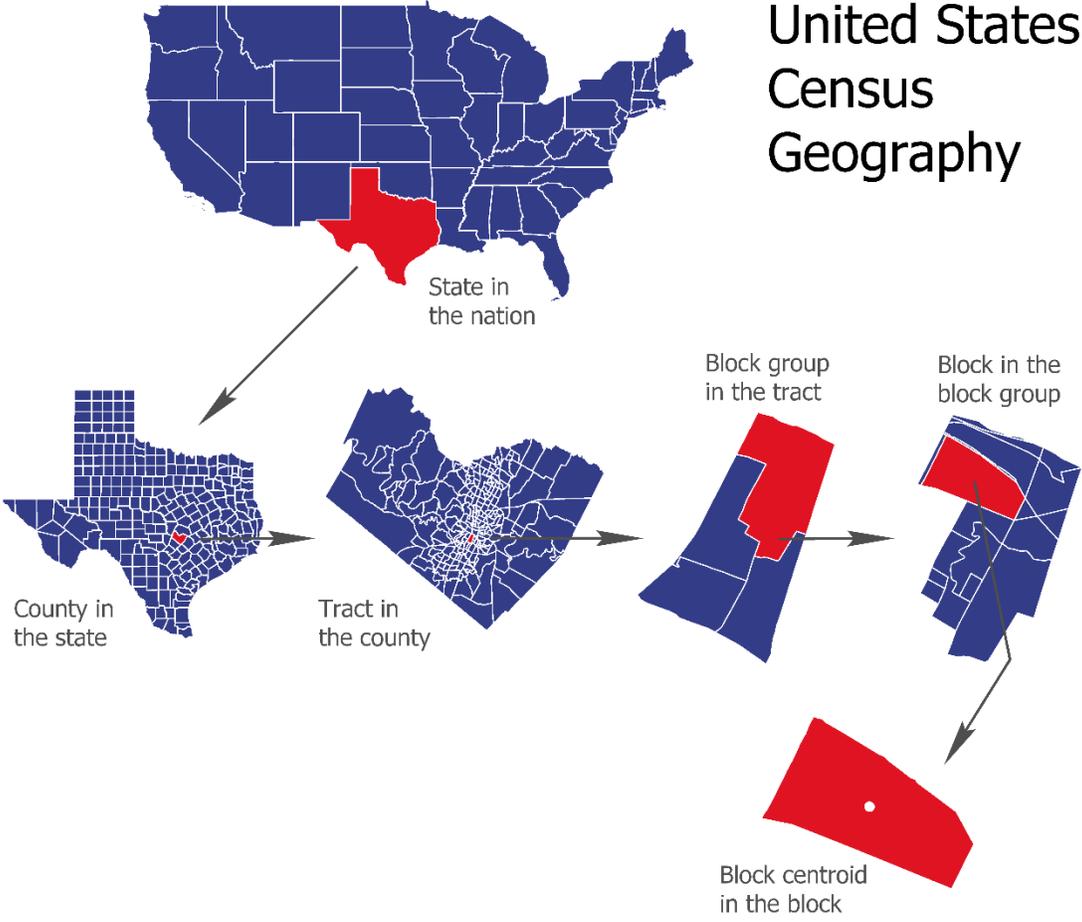
(Source: Created by TTI using 2010 U.S. Census Data)

Figure 2. U.S. Census Bureau Standard Definitions of Areawide Geography
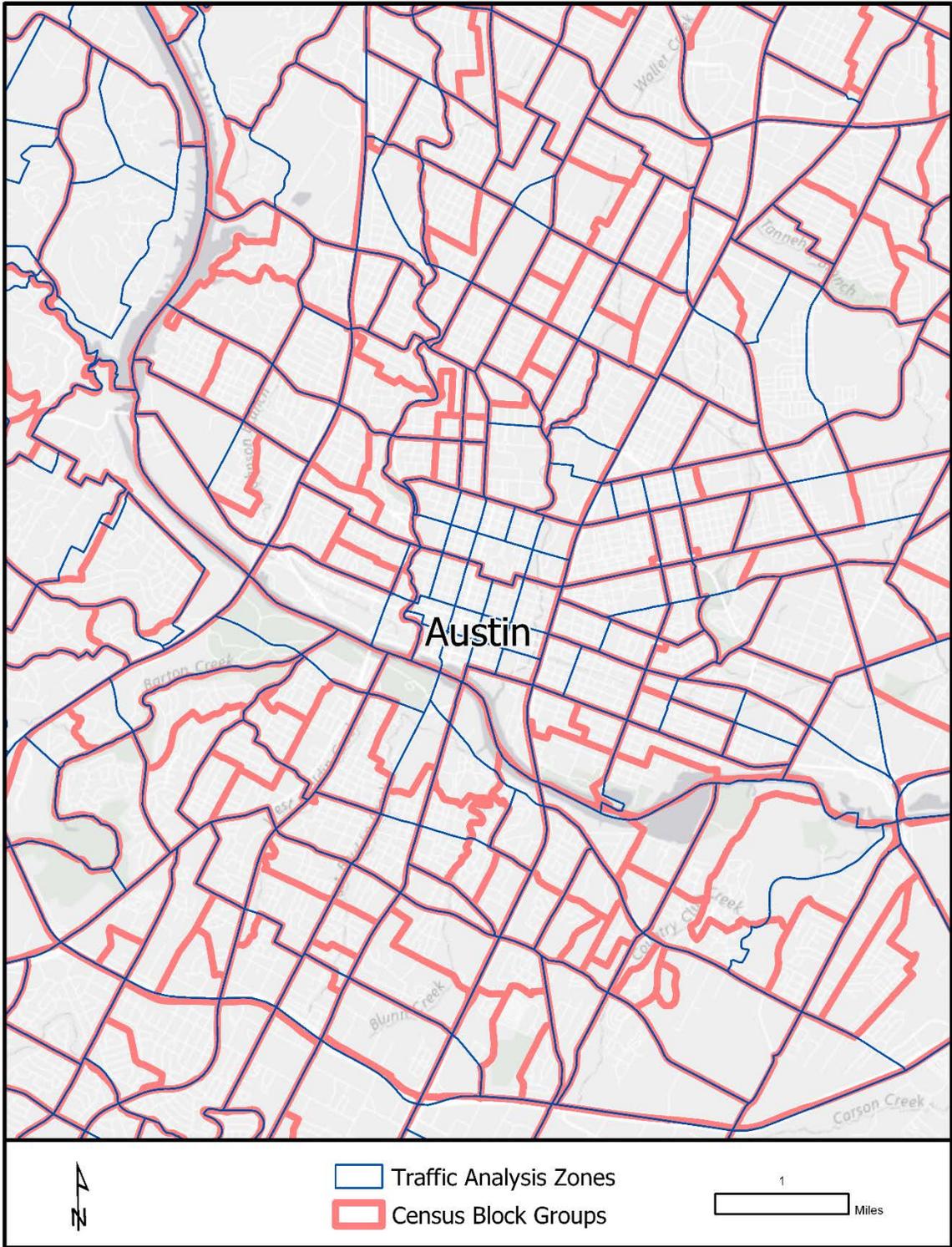
Figure 3. Visual Comparison of TAZs and Census Block Groups in Austin, Texas

When and Where Does Exposure Occur for Pedestrians and Bicyclists?

Most theoretical definitions of pedestrian and bicyclist exposure include references to contact with harmful vehicular traffic or opportunities for a pedestrian or bicyclist crash. For pedestrians, this occurs most explicitly during a street crossing. But several authors in the literature (Goodwin and Hutchinson 1977; Cameron 1982; Hauer 1982, Molino 2009; Elvik 2015) have posed a series of questions about when and where pedestrians or bicyclists can be considered "exposed". For example, are pedestrians "exposed" while walking along a sidewalk that is separated from motor vehicle traffic? Are pedestrians "exposed" if they cross the street but no motor vehicles are present at the time of their crossing? Are bicyclists "exposed" when they travel in a bike lane immediately adjacent to a motor vehicle travel lane, but then "not exposed" if they are riding in a separated bikeway? However, aren't bicyclists "exposed" in a separated bikeway when they cross intersecting streets and driveways?

In most cases, the feasibility and practicality of data collection has been used to operationalize this theoretical definition of exposure. Data cannot be collected on all pedestrian, bicyclist, and motor vehicle movements at all locations at all times. Therefore, most operational definitions of exposure have been based on pedestrian and bicyclist activity data that are already available (e.g., from travel surveys) or can be feasibly measured or estimated (e.g., from direct counts or models). Chapters 3 and 4 provide more detail on how various exposure analyses have constructed operational definitions of exposure based on the feasibility and practicality of data collection.

CHAPTER 3. EXPOSURE ANALYSIS AT AREAWIDE LEVELS

Pedestrian and bicyclist exposure to risk can be estimated and analyzed at numerous geographic scales. This chapter summarizes examples of exposure analysis conducted at areawide levels. In this chapter, areawide is a generic term that includes all geographic scales that are not facility-specific. The term areawide in this chapter includes several area scales, such as networks, neighborhoods, systems, regional, city, and state.

Exposure at areawide levels is usually measured or estimated at a macro-level. This is different than the facility-based exposure for an entire area, which is generally based on the micro-level point or segment data (e.g., pedestrian counts collected at intersections), but then aggregated to the wider area. This chapter focuses on areawide exposure analyses used in pedestrian and bicyclist safety analysis.

Summary of Practice

Table 1 provides examples of exposure analysis at areawide levels with the following information:
- **Reference:** Citation of each report or research paper.
- **Coverage:** The geographic size of each example's study area.
- **Development Scale:** The initial scale at which exposure is computed.
- **Data Sources:** The data used for exposure analysis.
- **Methods:** The methodology used for exposure analysis.
- **Unit of Exposure:** The definition of exposure as it relates to risk.

As can be seen from Table 1, studies varied in terms of their scales of exposure estimation, geographic coverage, data and methodologies as well as the units of exposure. While all studies were conducted at an aggregate level, some focused on a national level and some others performed their analysis for specific regions or communities. If a smaller scale area-level is used for the analysis, it is possible to apply the end result to a wider scale enlarging the analysis coverage. For example, Salon (2016) used Census tracts (a smaller scale than city or region) for her analysis, but then converted the estimates to a neighborhood level. This approach provided relatively more accurate estimates.

All the studies listed in the table have been eventually used in pedestrian and bicyclist safety analysis (e.g., estimating crash and/or injury rates). This was achieved by developing a variety of exposure measures in a given area, which can be mainly categorized as follows:
- Population: e.g., number of residents.
- Travelers: e.g., number of pedestrians.
- Trips: e.g., number of bike commuters.
- Distance: e.g., average miles walked.
- Time: e.g., total time traveled by a cyclist.

Table 1. Examples of Exposure Analysis at Areawide Levels

Reference	Coverage	Development Scale	Data Sources	Methods	Unit of Exposure
Chu 2003; Chu 2009	United States	Country	NHTS	Sketch planning	Population, number of hours traveled
Jacobson 2003	California cities, Danish towns, European counties, United Kingdom, Netherlands	City, county, country	Survey data - five different data sets for different areas (three population level and two time series); U.S. Census Journey to Work data (for California cities)	Sketch planning (including least squares analysis)	Kilometers walked/bike, portion journey to work trips for walk and bike
Blaizot et al. 2013	Rhône County, France	County	Regional and national household travel surveys	Sketch planning	Number of trips, distance traveled, time spent traveling
Rasmussen et al. 2013; Lyons et al. 2014	Columbia, MO; Marin County, CA; Minneapolis Area, MN; Sheboygan County, WI	Metropolitan statistical area, community	NHTS, ACS, annual count data for pedestrians and bicyclists	Sketch planning	Number of trips per mode, mode share, VMT
National Complete Streets Coalition 2014	United States	Metropolitan areas	NHTS, ACS	Sketch planning	Population, number or percent of people commuting by walk
Schneider et al. 2015	State of Wisconsin	State	ACS, State Intercensal estimates, and annual estimate of resident population, VMT	Sketch planning	Population, VMT, number of walk & bike commuters
Alluri et al. 2015	State of Florida	State	NHTS	Sketch planning	Population, number of walk trips
Retting and Rothenberg 2015	United States	State, country	U.S. Census Population	Sketch planning	Population
Salon 2016	State of California	Census tracts	NHTS, California household travel survey	Sketch planning (including cluster analysis)	Miles walked and biked
Alliance for Biking and Walking 2016	United States	State, country	ACS	Sketch planning	Population, number of walk & bike commuters
NACTO 2016	Multiple large US cities	City	ACS	Sketch planning	Number of cyclists
Guler and Grembek 2016	10 counties in California	County	Regional household travel surveys	Sketch planning	Total time traveled in million hours, total number of trips in millions

Greene-Roesel et al. (2007) and Molino et al. 2012 provided an extensive discussion on these exposure measures. As discussed by Greene-Roesel et al. (2007), choosing an appropriate measure depends on various factors including study purpose, methodology used, and location focused. For example, in his study, Chu (2003) suggested a time-based comparative approach to examine the fatality risk of walking. The results of this study indicated improvement when a time-based exposure measure is used instead of using only population-based measures. However, there were also limitations, such as the time-spent walking can be over-estimated in the surveys since "....people may perceive time spent on walking longer than it actually is…" (Chu 2003). A third factor to be considered is the availability of resources. While some measures might be more advantageous (or appropriate) to use than others, one might not have enough budget or time to collect or process more complex exposure estimates.

Guler and Grembek (2016) used two household travel surveys to estimate exposure by mode for ten counties in California in terms of: total time traveled in million hours and total number of trips in millions. The authors concluded that a time-based metric is more capable of capturing the different travel risk characteristics of different modes by comparing to a trip-based metric for each of the ten counties.

Summary of Data Sources and Methods

Data Sources
The main source of information for areawide exposure analysis is survey data, which facilitate the development of a variety of exposure measures described above (e.g., population). Given that most surveys used are able to provide detailed information on the characteristics of individuals and their trips, these exposure measures are also often studied by different characteristics, such as demographics (age, gender, etc.). In addition to regional travel surveys, in the United States, the two commonly used datasets for areawide exposure analysis include NHTS and ACS (described below). This section also describes a survey conducted by the National Highway Traffic Safety Administration (NHTSA) that is primarily focused on pedestrian and bicyclist attitudes, but also includes trip information.

National Household Travel Survey
Being the nation's inventory of daily travel, the NHTS is periodically conducted and provides detailed information to examine travel behavior of American public. The most recent published NHTS survey was conducted in 2009 and included 25,000 households representing all U.S. States and the District and Columbia (Santos et al. 2011). The data can be used to compute several different exposure measures (e.g. population, miles traveled) nationally or by major Census division. Additional add-on samples are also made available to the States and regional agencies for purchase. For example, "with the aim of supporting modeling efforts and examining travel behavior in Texas, the Texas Department of Transportation (TxDOT) purchased an additional sample of 20,000 households in Texas for the TxDOT NHTS Add-On Program in 2009 to go along with the sample of 2,255 households collected from the national survey" (Dai et al. 2014).These add-on samples provide the opportunity to populate different exposure measures at a finer geographic level and to develop more robust safety analysis, as also discussed in Edwards et al. (2012).

However, it is also important to recognize the limitations of the NHTS data that have been acknowledged by many researchers and practitioners in the field (see, for example Clifton and Krizek 2004; Sharp and Murakami 2005; Pucher et al. 2011; Salon and Handy 2014). While providing a rich national sample, the NHTS sample sizes might have sparse coverage at fine geographic scales particularly critical in the context of the current study. In their 2014 report, Salon and Handy (2014)

emphasized the difficulty of estimating bicycle and pedestrian activity due to lack of data coverage and indicated that "at the geographic resolution of the census tract, there are more than 2500 tracts that are not sampled at all by the NHTS, and only 15 of the sampled tracts include more than 30 household observations". According to the feedback received by the task force on Understanding New Directions for the National Household Travel Survey Transportation Research Board (TRB 2013), "the number of bicycle trips recorded is so low as to preclude almost any analysis". It was noted that several users requested a more representative sample of this special population to develop statistically reliable analyses. This and several other limitations have been discussed by the expert panel for the upcoming NHTS, which could help improve the current data issues (NHTS 2015, TRB 2016).

American Community Survey
While geographically covering the entire states, the ACS data differ from the NHTS as it provides information only pertaining to primary work commute trips (and for individuals aged 16+). ACS data are the replacement of the U.S. Census Journey to Work data, with improved sample design and data collection frequency. The ACS is an ongoing survey process, and the estimates are released each year based on the aggregated responses in 1-year, 3-years, or 5-years estimates. While the yearly estimates are available for areas of at least 65,000 people, the 3-year estimates are available for areas of at least 20,000. Starting with 2010, the 5-year estimates have begun to be available for all areas at smaller geographic scales including census tract and block group levels (the latter is the smallest geographic level available). As also demonstrated in McKenzie (2014), the ACS survey data provide several measures that can be used in an areawide exposure analysis for pedestrian and bicyclist safety, such as walking and bicycling commuting rates across cities in the nation.

The ACS provides an easy access to a regularly collected and nationally comparable measure of walking and bicycling data, but it is not without limitations as acknowledged by various earlier studies in the literature. As noted earlier, ACS data do not include all trips but instead it covers only work-related trips. This might become particularly problematic for exposure studies conducted in areas where non-motorized work trips do not provide a representative sample of overall biking and walking behavior. Another important limitation is related to the sampling such that ACS data might have high margin of error in areas where the number of surveys is low. Spielman et al. (2014) indicated that "the margins of error on ACS census tract-level data are on average 75 percent larger than those of the corresponding 2000 long-form estimate", while the initial expectations were 33 percent (Navarro 2012). This loss of precision led to significant difficulties in using the data (Spielman et al. 2014), which is likely be more of a concern for bicycle and pedestrian studies. Although aggregation of the data helps improve margin of error due to larger sample sizes, this approach may not be practical especially for local studies with smaller geographic areas.

While the uncertainty in ACS data has been frequently acknowledged, there has not been much effort to develop methodologies to overcome this limitation. Spielman and Folch (2014) developed "a spatial optimization algorithm that is capable of reducing the margins of error in survey data via the creation of new composite geographies, a process called regionalization". Spielman and Singleton (2015) suggested a "shift from a variable-based mode of inquiry to one that emphasizes a composite multivariate picture of census tracts", and applied this concept through a geodemographic typology across all census tracts in the United States. Bradley et al. (2016) developed a Bayesian approach to combine various surveys (including ACS) to "account for different margins of error and leverage dependencies to produce estimates of every variable considered at every spatial location and every time point". Wei et al. (2016) developed a classification method "to explicitly integrate errors of estimation in the assessment of

within-class variation and the associated groupings". Future research will greatly benefit to develop best practices and guidelines in accounting for large margin of error problems for smaller areas.

NHTSA Attitudes and Behavior Survey
Over the last fifteen years, NHTSA has administered two surveys that have been focused on better understanding bicyclist and pedestrian attitudes and behaviors. While providing valuable insights, these surveys have not been utilized for exposure analysis. The 2002 *National Survey of Bicyclist and Pedestrian Attitudes and Behaviors* included a representative sample of 9,616 U.S. residents aged 16 years or older, and it was conducted between June 11 and August 20, 2002 (Royal and Miller-Steiger, 2008). For the 2012 National Survey, a total of 7,509 interviews were conducted with residents aged 16 years or older between July 12 and November 18, 2012 (Schroeder and Wilbur, 2013a).

In general, both surveys included various questions related to the perceptions, attitudes and behaviors of bicyclists and pedestrians, and knowledge of infrastructure as well as the laws related to bicyclists and pedestrians. In addition, the surveys compiled several questions on bicycle and pedestrian trips focusing on the most recent date respondents bicycled and walked within the last 30 days (and over the summer months due to the timing of the survey). The 2012 survey also assessed the changes in bicycling and walking behavior and attitudes since 2002 (Schroeder and Wilbur, 2013b). Both surveys used a similar questionnaire for consistency and comparability (Schroeder and Wilbur, 2013c), and aimed at developing a better understanding on the attitudes and behaviors of bicyclists and pedestrian activities. However, "these data cannot be used to project year-round bicycling and walking behaviors" since it is generally a "reflection of biking and walking activity in the summer months" (Royal and Miller-Steiger, 2008).

Methodology
Exposure analysis at areawide levels is usually conducted through different versions of sketch planning methods to estimate nonmotorized activity/travel in an area. In most cases, sketch planning methods include simple computations and rules of thumb for quick estimations of population and travel behavior. These methods mostly depend on the available data (such as nationally collected survey data) and require little effort in terms of data collection and no specialized expertise. While the results are mostly in the form of aggregate level estimates with relatively low accuracy, they lead to simple and practical solutions especially when the resources (time, budget, staff, data, etc.) are limited.

Aggregate demand models also fall into areawide sketch planning methods as they are used to explain areawide activity levels of walking and bicycling based on aggregate characteristics (e.g. population density, employment density, median household income, land use diversity, etc.). These models are very similar to the direct demand models (described in Chapter 4 in details), and typically use regression models to quantify the relationship between overall bicycling or walking demand and the significant factors influencing that demand at a large spatial level. See for instance Barnes and Krizek (2005) for a bicycle demand model at a metropolitan statistical area level, and Ann and Chen (2007) for a nonmotorized demand model at a census block group level.

As part of the Nonmotorized Transportation Pilot Program (NTPP), Rasmussen et al. (2013) developed and applied a community-wide assessment method to examine the travel behavior changes with improved walking and biking infrastructure. As seen in Figure 4, their model was based on nationally collected data, including NHTS and ACS data, as well as annual counts for the community, and was used to estimate mode share changes and avoided VMT in the pilot communities. The model results were

also used to evaluate the safety implications by estimating the motorist-involved pedestrian and bicycle crash fatalities and reported injuries between 2002 and 2012 for pilot communities (Lyons et al. 2014).
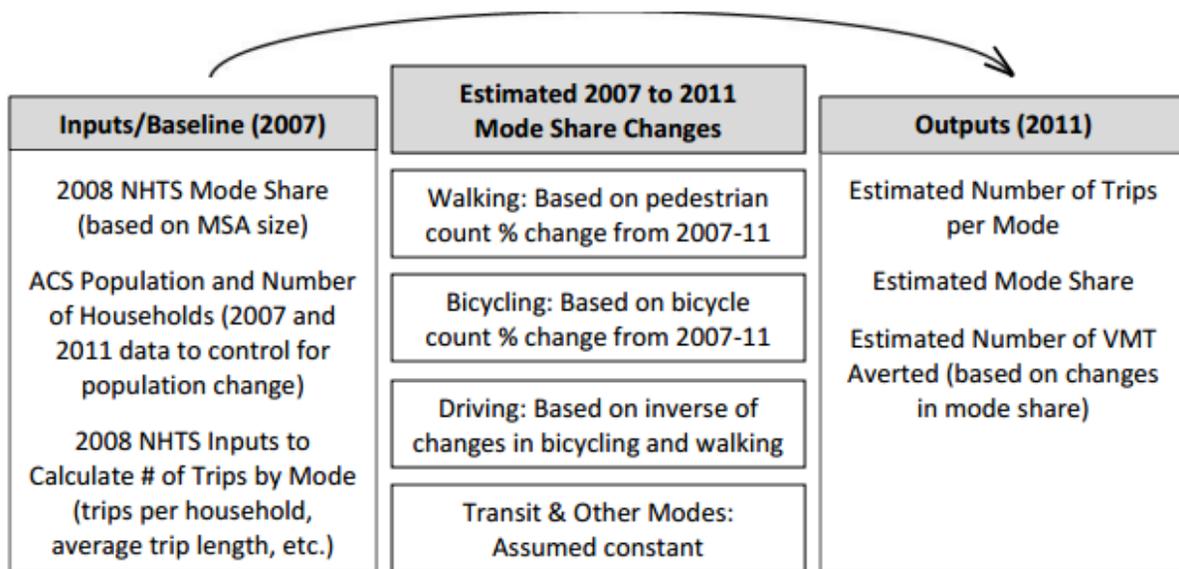
(Source: Rasmussen et al. 2012)

Figure 4. NTPP Model Framework

Jacobson (2003) used five different datasets to compute the amount of walking and bicycling and explore the collisions involving a motorist and a bicyclist or a pedestrian. His exposure analysis included different areas, including 68 California cities, 47 Danish towns, 14 European counties, United Kingdom, and Netherlands based on the following exposure measures:

- California Cities:
  - Portion journey to work trips on foot
  - Portion journey to work trips on bicycle
- Danish Towns:
  - Kilometers walked/capita/day
  - Kilometers bicycled/capita/day
- European countries:
  - Kilometers bicycled/capita/day
  - Trips on foot/capita/day
  - Trips on bicycle/capita/day
- United Kingdom and Netherlands:
  - Billion kilometers ridden annually

Using these exposure measures, he computed injury or fatality rates (based on the data available). For instance, for California cities, "injury incidence rates were calculated using the U.S. census population estimates as adjusted by the State of California's Department of Finance for year 2000".

The other studies exemplified in Table 1 also used regional or national surveys to estimate exposure measures at areawide levels using similar sketch planning tools. For example, Blaizot et al. 2013 used a

regional household travel survey data as the primary data to estimate exposure measures including number of trips, distance traveled and time spent traveling. Since the data were collected between November 2005 and April 2006, during the analysis stage, the seasonality of the regional data were corrected using the NHTS that covered an entire year. The injury rates were estimated for different road users by "dividing the number of injuries by the exposure measurement, and scaled per 1 million trips, kilometers or hours". These rates were also disaggregated by demographic characteristics (gender and age groups) and location characteristics (dense areas and non-dense areas).

In another study, Schneider et al. (2015) used simple computations to estimate pedestrian and bicycle crash rates in the state of Wisconsin (e.g. crashes per 100,000 people, crashes per 1,000 walk commuters, etc.) based on state level mileage and VMT data as well as national data, including US Census State Intercensal Estimates, Annual Estimates of the Resident Population and ACS. Similarly, Retting and Rothenberg (2015) used the U.S. Census population data as an exposure measure to compute pedestrian fatality rates (per 100,000 population) in all states of the United States. Alluri et al. (2015) used exposure measures of population (i.e. crashes per million) and number of walk trips (i.e. crashes per million walk trips) to compute crash rates (by age) in the state of Florida using the 2009 NHTS data. Using the 2001 NHTS data, Chu (2003) computed the nationwide fatality rates based on population (i.e. number of deaths per 100,000 population), and time spent walking (i.e. number of deaths per 10 million hours). Using the same NHTS dataset, Chu (2009) used time-based exposure measures for walking (time spent on access to or egress from another mode, time spent waiting for transit vehicles as exposure for walking) and computed the expected injury costs averaged over $2.00 per hour of exposure for walking and motoring.

In addition, in their analysis, National Complete Streets Coalition (2014) used both NHTS and ACS data to develop population-based exposure measures (e.g. number of commute walkers), which were used to evaluate pedestrian fatalities for various metropolitan areas. Likewise, Salon (2016) also used both the 2009 NHTS and 2010–2012 regional household travel survey data as a primary source of exposure data in California. Different than the previous studies described, she adopted relatively more advanced sketch planning methodology based on a small area estimation method as an improvement on per capita estimates at the regional or statewide levels. In her study, the production scale was census tracts, which were then used to develop cluster-based neighborhoods. She computed several exposure measures, including average walking and biking per different demographics (age and gender) and neighborhood types, and used category averages to estimate walking and biking by census tracts. These measures were then used to explore the crash rates at a more detailed geography.

Similar exposure measures have also been adapted in two recent reports. In their most recent benchmarking report, Alliance for Biking and Walking (2016) used ACS data and calculated pedestrian and bicyclist fatality rates for the states and the nation based on population-based exposure measures. These included fatality rates per million population (also categorized by age) and per 10,000 walking or bicycling commuters in the United States. The National Association of City Transportation Officials (NACTO) (2016) also used ACS data (i.e. number of cyclists) to compute risk of injury or death to cyclists. The exposure analysis was conducted citywide for seven cities, including Chicago, Minneapolis, New York City, Philadelphia, Portland, OR, San Francisco and Washington, D.C.

Summary and Conclusions

Exposure analysis at areawide levels is conducted at a larger scale (e.g. regional, statewide, or citywide) and adopts aggregate-level exposure measures (e.g. total number of people walking in a city). The choice of an appropriate exposure measure depends on various factors: study purpose, methodology, location of the analysis, and available resources. The main data source used for these types of analyses is the survey data. In addition to the local regional travel surveys, the NHTS and ACS have been used as key input for areawide exposure analysis. In pedestrian and bicyclist safety literature, areawide exposure analyses are mainly based on sketch planning method including aggregate demand models. These methods are composed of simple computations, do not require specific software or expertise, and are based on available data. Therefore, they provide practical and easy-to-apply solutions but with relatively low level of accuracy.

CHAPTER 4. EXPOSURE ANALYSIS ON SPECIFIC TRANSPORTATION FACILITIES

This chapter summarizes examples of exposure analyses conducted on specific transportation facilities. In some cases, exposure estimates are calculated for specific facilities, but also aggregated to various areawide geographies. For the purposes of this report, the examples of exposure analysis have been included in either Chapter 3 or 4 according to the most granular scale at which exposure estimates are produced.

Summary of Practice

Increasingly, public agencies are conducting regular counts and intercept surveys as part of routine pedestrian and bicyclist monitoring programs to monitor changes in behavior and volume. Over the years, there has been an attempt to standardize the collection and reporting of this pedestrian and bicyclist count data, first through Alta/ITE's National Bicycle and Pedestrian Documentation Project, FWHA's Traffic Monitoring Guide (TMG), NCHRP 797 report, and most recently through the FHWA's Exploring Pedestrian Counting Procedures report.

These count and direct measurement methods enable communities and regions to quantify exposure at a granular scale: points (i.e., intersection or mid-block crossings) and segments. However, pedestrian and bicyclist counts are most often conducted as a sampling at a limited number of locations within a city, so directly measured counts are not available for network or areawide exposure estimation. The limited number of counts could, nevertheless, be used as model inputs for estimating exposure at an aggregate scale for an entire area. Therefore, counts of pedestrian and bicyclist volumes can play the following roles in the development of exposure estimates:
- Directly measuring exposure on specific facilities.
- Calibrating network and regional models that estimate exposure at various geographic scales, ranging from specific facilities to various areawide geographies.

Table 2 provides a summary review of existing and proposed methods of directly measuring and estimating exposure on specific transportation facilities. Table 2 provides the following information for each example:
- **Reference:** Citation of each report or research paper.
- **Development Scale:** The initial scale at which exposure is directly quantified.
- **Coverage:** The geographic size of each example's study area.
- **Data Sources:** The data collected to either directly measure or estimate exposure.
- **Methods:** The type of model used to estimate exposure at various scales.
- **Unit of Exposure:** The definition of exposure as it relates to risk.

Table 2. Examples of Exposure Analysis on Specific Transportation Facilities

Reference	Development Scales	Coverage	Data Sources	Methods	Unit of Exposure
Cameron 1982	Point, Segment	Sydney, Australia	Manual counts	--	Product of Pedestrian and Vehicle Volumes
Tobey, Shunamen, and Knoblauch 1983	Point, Segment	Five Standard Metropolitan; Statistical Areas	Manual counts & vehicle ADT	--	Number of Pedestrian-Vehicle (P x V) Interactions
Qin and Ivan 2001	Point	Rural areas in Connecticut	Manual counts, population & land use data	Direct Demand Model	Weekly Crossing Pedestrian Volume
Transport Research Laboratory 2001	Point, Segment	National & Local Levels within Europe	Regional or national travel surveys & direct counts	--	Million Kilometers of Travel
Raford and Ragland 2004	Point	Oakland, CA	Manual counts & census data	Network Analysis Model	Average Annual Pedestrian Volume
Greene-Roesel, Diogenes, and Ragland 2007	Point, Segment	--	Direct counts, surveys, & census data	--	Number of Pedestrians; Trips; Distance Traveled; Time Spent Traveling
Molino et al. 2009 Molino et al. 2012	Point, Segment	Washington, D.C.	Manual counts & crossing distances	Direct Demand Model	100 Million Miles Traveled
Papadimitriou, Yannis, and Golias 2012	Segment	Athens CBD, Greece	Manual field surveys & counts	Discrete Choice Model	Vehicles Volume; Encountered While Crossing; Product of Vehicle; Volume and Pedestrian Crossing Time
Schneider et al. 2012	Point	San Francisco, CA	Manual & automated counts	Direct Demand Model	10 Million Crossings
Schneider, Grembek, and Braughton 2013	Point	UC Berkeley Campus Boundary	Manual & automated counts	--	10 Million Crossings
Strauss, Miranda-Moreno, and Morency 2013	Point	Montreal, QC, Canada	Manual counts	Direct Demand Model	Million Cyclists or Pedestrians per Unit of Time
Strauss, Miranda-Moreno, and Morency 2014	Point	Montreal, QC, Canada	Manual counts	Direct Demand Model	Million Cyclists or Pedestrians per Unit of Time
Hankey and Lindsey 2016	Point, Segment	Minneapolis, MN	Manual counts, census & land use data	Direct Demand Model	Bicycle & Pedestrian Volumes
Liggett et al. 2016	Point, Segment	Los Angeles County, CA	Manual counts	--	Average Number of Riders
Radwan et al. 2016	Point, Segment	State of Florida	Direct counts, population, distance crossed, vehicle ADT	Direct Demand Model	Million Pedestrian Miles Crossed per Entering Vehicle; 100 Million Vehicle Miles; Million Pedestrian Miles Crossed per Entering Vehicle
Wang, Lindsey, and Hankey 2016	Point, Segment	Minneapolis, MN	Manual counts	Direct Demand Model	Bicyclist Volumes

Note: -- indicates that the item did not pertain to the particular study.

Development Scales

Regarding direct measurement of exposure on specific transportation facilities, it is important to know at what spatial scale the measurements were initially developed for a particular application. The development scale determines the ultimate application scale at which exposure can be applied or estimated for locations without direct measurements. Table 2 offers a summary of the development scales for several nonmotorized exposure studies and applications by using the Highway Capacity Manual (HCM 2010) roadway system elements as levels of scale: points (i.e., intersections), segments, facilities, corridors, areas, and systems. More information on these types of roadway system elements can be found in Chapter 2 of this report.

For the examples listed in Table 2, the exposure development scales varied based upon the type of data source and collection method, modelling efforts, and the intended application of the resulting exposure measure. However, all of the examples utilized direct measurement of nonmotorized volumes at either the **point** or **segment scales** as their unit of exposure on specific transportation facilities (Papadimitriou et al. 2012; Qin and Ivan 2001; Raford and Ragland 2004; Schneider et al. 2012, 2013, Strauss et al. 2013, 2014). A majority of the examples used exposure measurements at both the point and segment scales since their respective applications accommodated the scales either separately (Liggett et al. 2016; Radwan et al. 2016; Wang et al. 2016) or were aggregated (Cameron 1982; Greene-Roesel et al. 2007; Hankey and Lindsey 2016; Lyons et al. 2014; Molino et al. 2009, 2012; Rasmussen et al. 2013; Tobey et al. 1983; Transport Research Laboratory 2001).

There is a close connection between the exposure development scale and the data sources used. Direct measurement of nonmotorized exposure is typically represented as pedestrian and bicyclist traffic volumes recorded through direct counts (manual or automated) at either points or segments. Alternatively, a variety of the examples incorporated some form of exposure estimation via a direct demand or choice model that use additional data sources other than just counts (Hankey and Lindsey 2016; Lyons et al. 2014; Molino et al. 2009, 2012; Papadimitriou et al. 2012; Qin and Ivan 2001; Radwan et al. 2016; Raford and Ragland 2004; Rasmussen et al. 2013; Schneider et al. 2012; Strauss et al. 2013, 2014; Wang et al. 2016). Keep in mind that the models still required a representative, random or non-random sample of nonmotorized count data for the scale at which exposure was estimated, i.e., intersections (i.e., points) and segments.

Units of Exposure

Greene-Roesel et al. (2007) states that "there is no single best definition of pedestrian exposure"; the same can be said about bicyclist exposure. In epidemiology, a general definition of exposure is contact with or proximity to a potentially harmful agent or event (Last et al. 1995). Table 2 shows that, within pedestrian and bicyclist exposure can be defined and measured in a variety of ways.

As illustrated in the previous section on development scale, the components of a safety study or risk assessment are closely interrelated and in some cases mutually exclusive. Being that the unit of exposure is an important component, it is directly dependent upon other aspects of the study, such as: development scale, target population, estimation methods, geographic area, available resources, purpose, etc. Therefore, the unit of exposure that best fits the needs and purposes of the study should be chosen (Greene-Roesel et al. 2007).

Tables 3 through 7 were adapted from Greene-Roesel et al. (2007) to help practitioners choose the appropriate unit of exposure for nonmotorized travel modes. These tables help to summarize the appropriate uses and the pros and cons of each generalized form of exposure related to nonmotorized

travel: volume, distance, and time. Note that the population and trips exposure measures are best used for aggregate level estimations, such as neighborhoods, cities, regions, etc., which was discussed in Chapter 3.

Table 3. Exposure Based on Volumes/Counts
(adapted from Greene-Roesel et al. 2007)

Appropriate Uses	✓ Estimating pedestrian and bicyclist volume and risk in a specific location. ✓ Assessing changes in pedestrian volume or characteristics due to countermeasure implementation at that site.
How Data are Gathered	✓ Manual or automated counts of bicycles and pedestrians. ✓ Typically a daily count, and sometimes an annualized estimate
Pros	✓ Counts are simpler to collect than other measures such as time or distance walked or biked. ✓ Automated methods for counting number of bicycles and pedestrians are improving.
Cons	✓ Does not account for the amount of time spent walking or biking nor the distance. ✓ Not easily adapted to assess exposure over wide areas (for example, a city).
Common Measures	✓ Number of bicycles and/or pedestrians per time period. ✓ Number of crossings. ✓ Average daily, weekly, or annual volume per point or segment. ✓ Product of bicycle or pedestrian and vehicle volumes (interactions).

Table 4. Exposure Based on Distance
(adapted from Greene-Roesel et al. 2007)

Appropriate Uses	✓ Estimating exposure at the micro or macro level. ✓ Estimating whether risk increases in a linear manner with distance traveled. ✓ Assessing how crossing distance affects risk.
How Data are Gathered	✓ For individual level exposure, through travel surveys. ✓ For aggregate level exposure, measurement of the length of the area of interest, combined with a manual or automatic count of the number of pedestrians.
Pros	✓ Can be used to measure exposure at the micro and macro levels ✓ More detailed than pedestrian volumes or population data ✓ Can be used to compare risk between different travel modes ✓ Common measure of vehicle exposure
Cons	✓ Does not take into account the speed of travel and thus cannot be reliably used to compare risk between different modes (e.g. walking and driving) ✓ Assumes risk is equal over the distance walked ✓ Must typically assume that each bicycle or pedestrian travels the same distance in a crossing, along a sidewalk, street, bike lane, etc.
Common Measures	✓ Miles traveled (total or average) per pedestrian. ✓ Miles crossed (total or average).

Table 5. Exposure Based on Time
(adapted from Greene-Roesel et al. 2007)

Appropriate Uses	✓ Estimating total pedestrian and bicyclist time exposure for specific locations. ✓ Comparing risks between different modes of travel (e.g. walking vs. riding in a car). ✓ Estimating whether risk increases in a linear manner with walking time. ✓ Comparing risk between intersections with different crossing distances and between bicycles or individuals with different travel speeds.
How Data are Gathered	✓ The number of bicycles or persons passing through an area multiplied by the time traveled. ✓ Time spent on walking activities reported on surveys.
Pros	✓ Accounts for different walking speeds ✓ Allows for accurate comparison between different modes of travel. ✓ Can be used to measure exposure at the micro and macro levels ✓ More detailed than pedestrian volumes or population data
Cons	✓ Time based measures assume risk is equal over the entire distance of a crossing. Only a small portion of time spent walking on roadways represents real exposure to vehicle traffic. This portion would include time spent crossing roads, walking on the road surface, or possibly walking along the roadside where there are no curved sidewalks (Chu 2003). ✓ Time spent on walking can be overestimated in surveys, because people perceive that they spend more time walking than they actually do (Chu 2003). ✓ Walking may be under-reported in surveys, because people may forget walk trips or may purposely choosing not to report. Both of these reasons are related to the fact that walking trips are relatively short. These very short trips may not register in the memory of respondents or the respondents may think that these short trips are unimportant (Chu 2003).
Common Measures	✓ Amount time traveling (total or average). ✓ Amount time crossing an intersection (total or average).

Table 6. Exposure Based on Trips
(adapted from Greene-Roesel et al. 2007)

Appropriate Uses	✓ Assessing pedestrian and bicyclist behavior in large areas, such as cities, states, or countries. ✓ Examining changes in pedestrian and bicyclist behavior over time. ✓ Making comparisons between jurisdictions. ✓ Assessing common characteristics of walking trips, such as purpose, route, etc.
How Data are Gathered	✓ Data are gathered through use of travel surveys.
Pros	✓ Appropriate for use in large areas. ✓ Best metric to assess relationship of walking with trip purpose. ✓ Trips can be assessed as a function of person, household and location attributes.
Cons	✓ As with most surveys, a large number of respondents are needed to adequately represent the underlying population. ✓ Less meaningful at the level of detail needed to assess risk at specific locations. ✓ Pedestrian trips are often underreported in surveys (Schwartz and Porter 2000).
Common Measures	✓ Number of trips (total or average) possibly by purpose.

Table 7. Exposure Based on Population
(adapted from Greene-Roesel et al. 2007)

Appropriate Uses	✓ Used as an alternative to exposure data when cost constraints make collecting exposure data impractical. ✓ Used to compare jurisdictions over time because population data are available for many geographies and time periods.
How Data are Gathered	✓ Population data for most cities is available on an annual basis through the ACS.
Pros	✓ Easy and low-cost to obtain; available for most geographies and time periods. ✓ Adjusts for differences in the underlying resident population of an area – for example, sparsely populated suburbs versus densely populated inner-city areas. ✓ Provides a crude adjustment for amount of vehicle traffic on the streets, since areas where more people live also tend to be areas where more people drive. ✓ May be the only way to represent exposure if direct measurements cannot be taken.
Cons	✓ Does not accurately represent pedestrian and bicyclist exposure. ✓ Does not account for the number of people who travel as bicyclists or pedestrians in the area. ✓ Does not provide information about amount of time or distance that members of the population were exposed to traffic.
Common Measures	✓ Number of people in a given area: neighborhood, city, county, state or country. ✓ Number of people in a particular demographic group: by age, sex, race, immigrant status or socioeconomic status.

Applications

The applications of nonmotorized exposure presented in Table 2 are centered on producing relative risk metrics (e.g., crash rates) that can help to make sense of pedestrian and bicyclist crash data. Many cities and states have pedestrian and bicyclist crash data but no way of understanding whether or not relative risk has changed. Numerous examples in Table 2 focused on developing crash rates for segments, intersections, or both for particular study areas like a city or county (Liggett et al. 2016; Radwan et al. 2016; Raford and Ragland 2004; Schneider et al. 2012, 2013, Strauss et al. 2013, 2014; Wang et al. 2016). Others used nonmotorized exposure to assess risk for other purposes, such as: trends over time for an area (Lyons et al. 2014; Rasmussen et al. 2013), before-and-after studies for new countermeasures (Molino et al. 2009, 2012), crash rates by time of day (Schneider et al. 2013), and cost-benefit analysis of safety measures (Transport Research Laboratory 2001).

Summary of Data Sources and Methods: Direct Measurement

The most direct form of measurement or nonmotorized travel exposure are pedestrian and bicyclist traffic counts. To help communities develop nonmotorized count programs there has been an attempt to standardize the data collection and reporting efforts, first through the Alta and Institute of Transportation Engineers (ITE) National Bicycle and Pedestrian Documentation Project (NBPD), FWHA's Traffic Monitoring Guide (TMG), NCHRP 797 report, and most recently through the FHWA's Exploring Pedestrian Counting Procedures report. These references are summarized below. This direct measurement approach (calculating exposure from systematic traffic monitoring programs) is the current state-of-the-practice for motor vehicle exposure estimation.

The NBPD is a count and survey effort designed to provide a consistent model of data collection and ongoing data repository for use by local agencies and organizations. Since 2003, the NBPD objectives have been the following (Alta Planning & Design and Institute of Transportation Engineers 2009a):
- Establish a consistent national pedestrian and bicyclist count and survey methodology, building on the 'best practices' from around the country, and publicize the availability of this free material for use by agencies and organizations on-line.
- Establish a national database of pedestrian and bicyclist count information generated by these consistent methods and practices.
- Use the count and survey information to begin analysis on the correlations between various factors and pedestrian and bicyclist activity. These factors may range from land use to demographics to type of new facility.

The NBPD data collection effort is split into counts and surveys as follows:
- The count effort conducts screen line and crosswalk counts to measure activity levels at the same location over time and allows for associative research between variables (such as demographics, facility, land use, etc.) and activity volumes (Alta Planning & Design and Institute of Transportation Engineers 2009b).

- The survey effort, based on intercept surveys, ask randomly selected people for their trip purpose, length, and other information while they are in the middle of making those trips (Alta Planning & Design and Institute of Transportation Engineers 2009b).

The official national count and survey days are Tuesday through Thursday and the following Saturday of the second week in September. A description of the facility, location, and methodology should accompany any data to allow analysis of the relationship between biking and/or walking rates and demographic and/or geographic factors. A variety of materials are offered for download on the NBPD's website.

In 2006, Caltrans selected the NBPD as the data collection methodology for the Seamless Travel research study in San Diego County (Jones et al. 2010). Also in 2006, the FHWA Volpe National Transportation Systems Center chose the NBPD as an evaluation methodology for the Nonmotorized Transportation Pilot Project (Lyons et al. 2014). The 2013 TMG references NBPD guidance for short-duration counts, counter positioning, count duration determination, and months/seasons of year for data collection (Federal Highway Administration 2013).

The 2013 TMG includes chapter 4 that is dedicated to nonmotorized traffic monitoring, which encompasses bicycles, pedestrians, and other nonmotorized road and trail users (Federal Highway

Administration 2013). The chapter emphasizes the challenges of collecting nonmotorized data as compared to established motorized data collection efforts, such as: the scale of data collection, higher use of lower functional class road and streets, greater amount of error from short duration counts, and quickly-evolving technologies and their unestablished error rates (Federal Highway Administration 2013). Several examples of data collection equipment are provided to help the users understand the strengths and limitations of each type of technology and what is appropriate for their situation and budget to ensure proper counts. The chapter provides guidance on what to consider when developing a nonmotorized traffic data collection program that includes both continuous and short-duration count locations. Topics such as data management, site selection, variability, count duration, and factoring (correction and expansion) are all summarily discussed.

The NCHRP 797 Report Guidebook on Pedestrian and Bicycle Volume Data Collection published in 2014 is the most comprehensive resource on pedestrian and bicycle volume data collection that is currently available (Ryus et al. 2014). The objectives of the guidebook are to help practitioners understand the value of nonmotorized data, develop a collection plan, identify the most appropriate method, and how to account for error introduced by counting technology (Ryus et al. 2014). The guidebook does not cover trip sampling techniques, presence detection, and trip generation estimation, but instead it specifically focuses on methods for counting the actual number of pedestrians and bicyclists crossing a screenline or intersection. The NCHRP 797 report complements the TMG Chapter 4 by expanding on the accuracy of different counting technologies accompanied by real-world examples of counting applications. One of the several example applications provided is safety analysis where a measure of exposure is necessary to make sense of crash data and assess risk relative to volume(s), i.e., exposure. No explicit definition of exposure is provided; however, the report explains that "exposure relates to the frequency of a bicyclist or pedestrian being present in a conflict zone with the potential to be involved in a crash" (Ryus et al. 2014).

In May 2016, FHWA published the *Exploring Pedestrian Counting Procedures* report (Nordback et al. 2016). This report expands on the existing guidance and best practices listed above to recommend strategies for accurate, timely, and feasible measurement of pedestrian travel (Nordback et al. 2016). The authors offer five key recommendations based on review of the current practice and webinar and interview responses (Nordback et al. 2016):
1. Expand the use of multi-day/multi-week counts to reduce estimation error rates, and rotate counts around the network;
2. Validate equipment at installation and regularly thereafter;
3. Tailor quality checks appropriate for low volume versus high volume locations;
4. Compute bias compensation factors (e.g., occlusion adjustment factors) to account for limitations related to equipment and locations; and
5. Conduct both short-duration and continuous counts to fully consider temporal and spatial aspects of pedestrian traffic patterns.

The report goes into great detail in describing the operation and management of pedestrian count data collection equipment and the subsequent data management in terms of count duration, validation, calibration, purchasing strategies, quality assurance/control, standardization, factoring, accessibility, and analysis. This is a key resource for practitioners interested in creating a pedestrian count program.

El Esawey et al. (2015) is a noteworthy example of direct measurement, in which various short-duration bicyclist counts conducted in Vancouver, British Columbia, in various months and years have been assembled to provide one of the most compete estimates of bicyclist traffic on a street network in a

major North American city. In particular, the authors indicate that bicyclist risk exposure is a key application of their bicyclist count database. The paper by El Esawey et al. illustrates the challenges that public agencies face in creating a facility-specific bicyclist and pedestrian count database for an entire citywide street network that is based solely on direct measurement. Because of these challenges, some exposure analyses have tried to supplement the limited number of direct pedestrian and bicyclist counts with model estimates, which is the topic of the next section.

Summary of Data Sources and Methods: Estimation

In addition to direct measurement methodologies, exposure analysis at the facility or segment-level can be performed using estimation or modeling-based methodologies (see Figure 5).
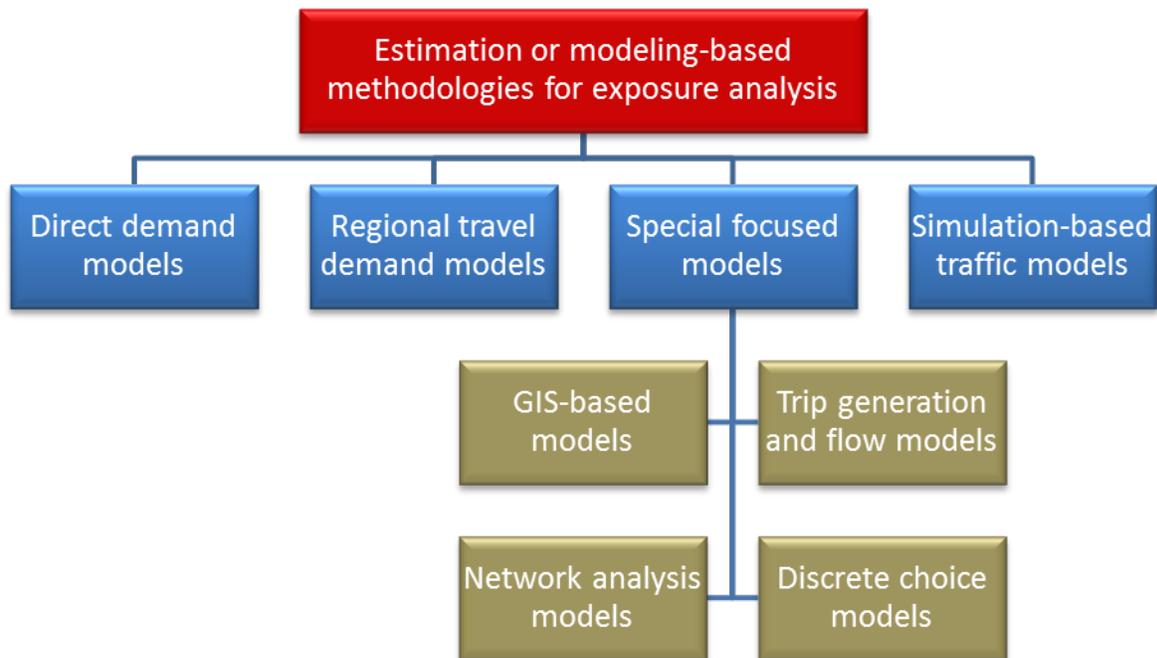
Figure 5. Estimation Methods That Have or Could Be Used For Exposure Analysis

Direct (facility) demand models have played a major role in the area of bicycle/pedestrian safety whereas the other modeling types have been used infrequently or not at all. An overview of all these potential models is provided here for completeness. Given the focus of the pedestrian and bicyclist safety analysis, example studies provided in Table 2 are discussed in more details.

Direct Demand Models
Direct demand models are among the most widely used tools in the literature for pedestrian and bicyclist volume estimation modeling (Pulugurtha et al. 2006; Pulugurtha and Repaka 2008; Schneider et al. 2009; Griswold et al. 2011; Strauss and Miranda-Moreno 2013; Tabeshian and Kattan 2014; Fragnant and Kosckelman 2016; Schmiedeskamp and Zhao 2016). These models have been primarily used to develop facility-demand estimations for the local level of community, project, and facility planning. The FHWA has released a Non-Motorized Travel Analysis Toolkit, which includes various applications to support non-motorized transportation planning and modeling. This Toolkit includes several direct demand models to estimate pedestrian and bicycle volumes (FHWA 2016). Direct demand models have

also served as the primary tools to measure bicyclist and pedestrian exposure for safety analysis. As discussed in Chapter 3, aggregate demand models are also similar to direct demand models though the analysis is performed at a larger level (e.g., regional level) using aggregate characteristics.

Direct demand models are generally based on different versions of regression modeling to explain "demand levels as recorded in counts as a function of measured characteristics of the adjacent environment" (Kuzmyak et al. 2014). For example, researchers from the University of Minnesota (Lindsey et al. 2012; Hankey et al. 2012) have developed several count-based pedestrian and bicyclist models to estimate nonmotorized traffic in Minneapolis, Minnesota using ordinary least squares and negative binomial regression. While neighborhood design and urban form were found to be more significant for estimating bicycle traffic, road classification, proximity to amenities and activity centers were identified as significant independent variables for pedestrian traffic. As part of Seamless Travel Project, Jones et al. (2010) developed pedestrian and bicyclist demand models to estimate volumes at intersections during 7 to 9 A.M. periods in San Diego County. These models were constructed using 80 manual, five automatic machine count locations, and GIS data on land use, demographics, etc. Fehr & Peers (2010) also developed similar pedestrian and bicycle models to estimate volumes during 5 to 6 p.m. peak periods for Santa Monica.

Direct demand models are appealing due to their simplicity in development and application, and since they are generally based on available data. However, they are limited in terms of capturing the behavioral structure and also not transferable due to relatively limited sample size and characteristics that the models are built on (see also Kuzmyak et al. 2014 for a detailed discussion on the advantages and limitations of such models). Schmiedeskamp and Zhao (2016) explained such models as following "a similar approach of first proposing a set of explanatory variables, fitting some form of regression model, and then interpreting and justifying the results according to the guiding theory". Several different types and forms of explanatory variables have been used in the development of these models. The variables included but not limited to transportation system variables, built environment variables, socio-economic characteristics, weather and typology. The model variables showed some differences based on the mode (i.e. pedestrian model versus bicycle model) as well as the statistical model type. Several of the studies reviewed indicated the influential effects of density, accessibility and proximity on pedestrian models. In addition to similar neighborhood forms, bicycle models were found to be influenced by some other specific infrastructure and system characteristics, such as presence of bicycle lanes and traffic volume. The direct demand models have also been used for predicting volumes at locations where the count data are not available, extending the study to an areawide level in the application process. While several similar works have been developed over the last decades, the studies differ such that researchers work on improving the estimation results by developing models that are more meaningful, practically more applicable, and statistically more robust.

The examples discussed in this section are pedestrian and bicyclist safety analysis examples that include exposure. Schneider et al. (2012) developed and applied a pedestrian intersection volume model for San Francisco. A sample of counts at 50 intersections were collected and adjusted to produce annual pedestrian crossing estimates at each sampled intersection. Next, the authors developed a log-linear regression model to identify the relationship between annual pedestrian volume estimate and various different explanatory variables including land use, transportation system, local environment, and socioeconomic characteristics near each sampled intersection. The model was then used to evaluate pedestrian crossing risk at each intersection based on the exposure measure of the number of pedestrian crashes per 10 million crossings. Molino et al. (2009; 2012) also developed a log-linear regression model (with Poisson distribution) to estimate pedestrian counts at signalized intersections in

Washington, D.C. While 15-min pedestrian counts served as the dependent variable, the independent variables of the model included land use variables (e.g. commercial, residential) and characteristics of the day (e.g. day of the week, time of the day). Using the parameter estimates of the model and follow-up adjustment procedures, a total number of miles traveled were estimated "…by multiplying the total number of pedestrians by the mean width of all the sampled signalized intersections." This result was then used as an exposure measure in pedestrian crash rate computation.

Several others have followed similar approach in estimating bicycle or pedestrian volume exposure measures using direct demand models. For example, Qin and Ivan (2001) estimated a general linear model for rural areas of Connecticut. Their dependent variable was the weekly pedestrian volume crossing the street at 32 different sites. The estimated model indicated that the number of lanes, area type, and sidewalk system significantly associated with the estimated pedestrian volume, which was proposed to be used in analyzing pedestrian fatality and injury rates in a follow-up research. Abasahl (2013) developed linear and log-linear models for both pedestrian and bicycle volume estimation. Their dependent variables were pedestrian and bicycle volumes collected at 92 (signalized) intersections in four Michigan cities. The estimated model volumes were then used as exposure measures in crash analysis for each nonmotorized mode and for all cities in the study area. Using a count database of 954 observations and 471 locations, Hankey and Lindsey (2016) employed a stepwise linear regression model that allowed for varying spatial scale of independent variables including land use and transportation network variables. Relying on the modeled estimates of bicycle traffic from this latter work, Wang et al. (2016) then estimated peak-hour bicycle traffic volumes for many segments in Minneapolis. The model results were then converted to bicycling volume for intersections and used for computing bicycle crash rates by intersections and segments. Radwan et al. (2016) used a stepwise regression model to estimate intersection pedestrian volume (for 52 sample intersections). The model was based on three main independent variables: daily traffic volumes, distance crossed, and population. The model estimates were then used to classify intersections across the state of Florida to compute the statewide averages for pedestrian crash rates at intersections.

Strauss et al. (2013; 2014) used a relatively improved version of modeling to estimate nonmotorized demand. Strauss et al. (2013) developed a bivariate Bayesian Poisson model to simultaneously estimate cyclists' injury occurrence and bicycle activity at 647 signalized intersections on the island of Montreal, Quebec, Canada. In a follow-up study, Strauss et al. (2014) applied their Bayesian modeling methodology as part of a multimodal approach aimed at examining the safety at intersections for both nonmotorized and motorized traffic. After model calibration, the study compared injury and risk between modes and intersections by using the "expected number of injuries (obtained from the models) per million cyclists, pedestrians or motor-vehicle occupants per year" as the expected risk.

Regional Travel Demand Models

The state of practice mainly consists of regional travel demand models that are based on traditional trip-based forecasting models. The trip-based models generally consist of four main steps: trip generation, trip distribution, mode share, and traffic assignment. During the assignment step, the predicted traffic volumes are assigned to the individual network links (usually based on shortest distance). TAZs are the most commonly used geographic units to inventory existing and future demographic data required for modeling purposes. Therefore, trip-based models are particularly limited in estimating nonmotorized travel due to their coarse level of spatial analysis structure. Schneider et al. (2009) and Griswold et al. (2011) indicated that such regional demand models are not adequate in capturing the fine-grained differences in intersection-level bicycle or pedestrian activity. Kuzmyak et al. (2014) pointed out that "…if these models are used to account for nonmotorized travel, it is typically limited to the trip

generation step; nonmotorized trip productions and attractions are estimated, but they are then removed from the remainder of the analysis, which focuses on motor vehicle trips". Furthermore, Aoun et al. (2015) emphasized the lack of these regional models in capturing recreation trip purpose, which is a key consideration in pedestrian and bicyclist trip rates.

To overcome these limitations and increase their sensitivity to pedestrian and bicyclist trips, several enhancements have been made to trip-based models, such as developing an enhanced trip generation model sensitive to land use factors or an enhanced auto ownership model as input to nonmotorized trip production. Emerging tour- or activity-based models also provide superior alternatives to traditional four-step models since they are based on individuals rather than trips, and the spatial resolution can be reduced to a smaller level of geography (such as parcels instead of TAZs).

Special Focused Models

The literature has also witnessed various versions of specially focused models that can be particularly beneficial to be applied at the corridor and subarea planning level. These are primarily variations of focused regional model approaches. For example, the scenario planning tools, which heavily depend on the usage of **GIS-based modeling methodologies**, are used to estimate nonmotorized travel under alternative land use and transportation investment scenarios. The GIS-based walk-accessibility model developed by the NCHRP 08-78 research team provided an enhanced example to such tools, expanding their capability by estimating pedestrian trip tables using GIS-derived walk-accessibility scores. This model uses GIS to compute measures of accessibility to or from any point by all modes and attraction types, and then estimates mode split and creates walk trip tables by purpose (Kuzmyak et al. 2014).

Similarly, the **pedestrian trip generation and flow models** are among the examples of focused regional models specifically focusing on pedestrian travel and smaller geographical zones rather than TAZs. The two examples of this type of modeling include PedContext and its sequel Model of Pedestrian Demand (MoPeD), which were developed through the University of Maryland's National Center for Smart Growth. While PedContext is not publically available, MoPeD is an open source model designed to be used by practitioners and non-experts. The model requires data on vehicle ownership, street connectivity, parcel-level land use, Census population and employment, and travel survey. Kuzmyak et al. (2014) indicated that, compared to the NCHRP 08-78 GIS-based walk-accessibility model, MoPeD is limited since it only generates walk trips instead of developing an overall trip generation and mode choice model. In particular, MoPeD uses pedestrian analysis zones (which are block or street-level) as the level of analyses. The main modeling structure follows regional four-step process, but employed only for walk trips, yielding to a link and intersection activity levels for walk trips (see http://kellyjclifton.com/products/moped/). Clifton et al. (2008) indicated that the objective of the MoPeD study was to "develop a method to estimate pedestrian demand or pedestrian volumes on a network – in order to evaluate pedestrian risk exposure in Maryland communities".

Network analysis models can also be discussed under these special focused models since they usually use variations of the four-step modeling approach for trip generation and distribution (Raford and Ragland 2006). These models are based on a representation of a pedestrian network. They are used to estimate volumes for specific facility types (e.g. street segments or intersections) over an entire area of interest (e.g. neighborhood or city). Space Syntax is one of the most well-known examples of network analysis models, which was first developed in mid 1980s in London. The model framework has been widely used in planning projects in Europe and Asia, but relatively unknown in the United States (Raford and Ragland 2004; McDaniel et al. 2014). Kuzmyak et al. 2014 indicated two potential reasons for its relatively minimal usage: 1) The information on its special software is limited; and 2) The process is not

intuitive to transportation planners since its process does not follow traditional trip generation and distribution steps. Instead, it uses spatial characteristics and relationships to explain the route chosen. Raford and Ragland (2004) described space syntax as a "suite of modeling tools and simulation techniques used to analyze pedestrian movement and to predict pedestrian volume". The authors listed seven steps for creation of a space syntax predictive model (Raford and Ragland, 2006):

1. Base data collection
2. Pedestrian route network modeling
3. Processing for movement potentials
4. Collection of pedestrian counts to calibrate the model
5. Addition of land use, transit and other variables
6. Testing the accuracy of the model
7. Forecasting future pedestrian volumes based upon network changes

In one of their relevant studies, Raford and Ragland (2004) applied the space syntax model to estimate pedestrian volumes at 670 intersections (from a total of 42 intersections and 94 counts) for the City of Oakland, California. The output volumes were then used in a safety analysis for the city's first pedestrian master plan. In specifics, the relative risk used for the safety analysis was computed for each intersection by dividing the annual pedestrian-vehicle collisions by exposure measure (i.e. average annual pedestrian volume).

Finally, there have been few efforts using the underlying principles of **discrete choice models to model crossing behavior** based on the information about the crossings and crossing behavior during the trip as an exposure measure. Lassarre et al. (2007) explained that "accident risk exposure can be estimated for any location (micro-environment) along a pedestrian trip, where a pedestrian is likely to cross". This then requires development of a pedestrian behavior choice model for each location along an entire trip. Lassarre et al. (2007) used this concept in developing a framework for modeling pedestrian's exposure considering their crossing behavior. A nested logit model was utilized for developing a hierarchical choice structure between junctions and mid-block locations. The independent variables used included origins and destinations, traffic characteristics (e.g. traffic volume), and pedestrian facilities (e.g. pedestrian signal). The final estimated crossing probabilities were then used to compute accident risk exposure. Using a sequential logit model, Papadimitriou et al. (2012) followed a similar approach by first estimating crossing probabilities associated with each alternative location along a trip, and then estimating pedestrian exposure to risk based on this crossing behavior. A pilot model was applied to a pedestrian trip in Athens, Greece.

Simulation-based Traffic Models

Benefiting from advances in computation capabilities, simulation-based traffic models have also evolved substantially over the last two decades. These models differ from the travel demand models as they often use the traffic volumes output of the relevant travel demand models as inputs to the traffic simulation models (DKS et al. 2007). These models can be applied at microscopic, macroscopic, or mesoscopic levels. For example, Abdelghany et al. (2012) developed a mesoscopic simulation-based dynamic trip assignment model for large-scale pedestrian networks. Their model is responsive to predict pedestrian responses to changes in design, operational conditions, and crowd management. The authors indicated that "the model can configure the study area in the form of a network and represent pedestrian demand at the individual level". Hong et al. (2016) developed a pedestrian exposure model based on a hybrid microsimulation-statistical model that also accounts for heteroscedasticity and spatial correlation. They used data composed of pedestrian dynamics, pedestrian area dynamics, and network topology measures. The authors tested their methodology for modeling 688 crosswalks in Seattle

Washington using various network typology measures integrating centrality, clustering, attractiveness, etc.

In fact, the recent literature has witnessed development of various agent-based microsimulation models aimed at capturing pedestrian activity in an area. Raford and Ragland explained that these models are based on "simulation of individual pedestrian movement in crowds ("agents") based on complex behavioral rules and environmental modeling". Greene-Roesel et al. (2007) described these models as using "flow principles from physical science to model pedestrian behavior in confined spaces such as interior of shopping mass or subway stations, on a single or small number of streets, or within building interiors". Microsimulation models provide highly accurate, detailed, and visually strong pedestrian flow. On the other hand, they are complex and require significant input data and special resources, such as specialized software (e.g. VISSIM, PARAMICS, etc.) and unique expertise (Raford and Ragland 2006; Greene-Roesel et al. 2007).

Innovative Methods to Estimate Facility-Specific Exposure

Thus far, this chapter has focused on data sources and methods used by practitioners and researchers to directly measure or estimate facility-specific pedestrian and bicyclist exposure. However, there are several innovations that, if fully developed in the next five to ten years, have the potential to dramatically improve pedestrian and bicyclist activity data to estimate exposure for safety analyses. The next several sections describe these innovative methods and data sources.

Crowdsourcing from Mobile Devices

Many pedestrians and bicyclists carry a highly-advanced, location-aware sensor everywhere they go: their GPS-enabled smartphone (http://www.pewinternet.org/fact-sheet/mobile/). There are many commercial applications that rely on knowing the location of a smart phone to provide location-based services (such as Google Maps and Traffic, Facebook, TripAdvisor, etc.), and these companies are using petabytes of historical smartphone location information and advanced analytics to estimate activity levels at businesses and other points of interest (e.g., see Google's Popular Times feature). Other companies (such as Streetlight Data, Cuebiq, etc.) also work in this location analytics domain, and try to provide insights in real-world consumer behaviors and trends. It is important to note that some population groups (such as the elderly, poor, young children) may be underrepresented in smartphone activity data.

This type of smartphone monitoring is considered passive, in that the smartphone owner/user does not have to initiate an app in order for the smartphone location to be tracked (although location services does have to be enabled within the app's settings). With passive monitoring, the smartphone routinely stores and sends the smartphone location without owner/user intervention. Sometimes this occurs even when the smartphone app is not open or active (assuming that locations services are enabled). As one might expect, passive and anonymous monitoring of thousands or millions of location-aware smartphones over several months or years could lead to significant improvements in pedestrian and bicyclist activity data.

Another approach to smartphone monitoring is becoming more common in pedestrian and bicyclist planning. This approach, sometimes called active monitoring, relies on a smartphone owner/user to initiate a fitness-based app (such as Strava) or other trip/activity collector app (such as Moves) to gather walking, jogging, running, or bicycling activity. In other cases, a wearable fitness device (such as Fitbit)

could be used to gather route choice information from pedestrians or bicyclists. The user agreement for these apps includes a provision for the app to anonymously collect and reuse the smartphone location data. To date, Strava has been the most active app developer to resell this pedestrian and bicyclist activity data to public agency for planning purposes. Relative walking and bicycling activity levels of Strava users (i.e., Strava Heat Map) can be seen online at http://labs.strava.com/heatmap.

Both of these smartphone monitoring approaches have their strengths and limitations. Passive monitoring can provide larger and less biased samples of pedestrians and bicyclists, simply because it does not require the smartphone owner/user to initiate app-based location monitoring. But in some situations, it may be difficult to differentiate travel mode (e.g., bicyclists in slow-moving motor vehicle traffic). Active monitoring (such as Strava) can provide more detailed data about activity type (e.g., walking, jogging, bicycling, off-road bicycling) as well as demographics. However, the activity data from active monitoring is typically from a much smaller and more biased sample (e.g., recreation-based activity) (Griffin and Jiao 2016).

Advanced Video Image Processing

Image processing on video data or Google Street View uses machine learning algorithms to accurately identify a non-motorist from the field-of-view of video or images. Video-based and image-based human detection and counting have been studied by many researchers (Dalal and Triggs, 2005; Gallahar and Chen, 2009; Tan et al., 2011; Yin et al., 2015; Qi et al., 2016; Tome et al., 2016;). The common method applied in these studies by extracting the features from the images at first, and then utilizing different machine learning algorithms to perform a precise classification. Although researchers developed many high quality algorithms, exploration on pedestrian detection and count is still attracting many researchers as there is an ongoing demand for more accurate estimates.

The algorithm developed by Dalal and Triggs (2005) is considered as one of the most popular pedestrian detection algorithm. The detection was done by the histogram based on the gradient direction. Tan et al. (2011) developed semi-supervised elastic net to count pedestrians. The research team used sequential information between unlabeled samples and their temporally neighboring samples to perform the study. The developed method showed superior predictions than the other state-of-the-art studies. Yin et al. (2015) used Google Street View images to extract pedestrian counts using machine vision and learning technology. The reliability tests results showed that the developed method was adept in counting pedestrians with a reasonable level of accuracy. Qi et al. (2016) proposed a sparse representation based approach for pedestrian detection from thermal images. In this study, the researchers first adopted the histogram of sparse code to represent image features and then detected pedestrian with the extracted features in different frameworks. This study validated the approach by comparing with three widely used features: Haar wavelets, histogram of oriented gradients, and histogram of phase congruency. The results showed the superiority of the approach developed in this study. Tome et al. (2016) used the popular modern algorithm deep convolution neural network to detect pedestrians. The research team tested the developed algorithm on the core hardware of autonomous car technology.

Pedestrian Pushbutton Activations

Several studies have examined the feasibility of using pedestrian crosswalk pushbuttons to estimate pedestrian counts at intersections. In this method, the number of crosswalk actuations must be factored up to account for cases in which more than one pedestrian crosses during each pedestrian crosswalk

phase. Several studies attempt to characterize this relationship between signal actuations and actual pedestrian counts. In a limited pilot study in Portland, Blanc et al. (2015) finds 1.24 pedestrian crossings per pedestrian actuator press. Kothuri et al. (2016) also measure pedestrian actuated signal phases in Portland, Oregon. They show that is feasible to capture pedestrian actuated signal phases using existing technology and infrastructure for the evaluation of facility improvements. In NCHRP Report 797, Ryus et al. (2014) provide a thorough overview of actuation technologies for counting pedestrians and bicyclists. Day et al. (2014) present a statistical regression method to predict single actuator counts as a function of weather, time of day, facility characteristics, and land use. While signal actuation counts are a noisy estimate of pedestrian counts, Day et al. argue that the method is useful for the measurement of relative changes in exposure due an intervention. It is our conclusion that more research is needed before signal actuation methods are widely implemented.

Naturalistic Data Collection for Pedestrians and Bicyclists

Naturalistic data collection refers to the unobtrusive observation of behaviors. This approach has been used in many fields outside of transportation for quite some time. Advances in sensor, computer, and telecommunication technologies now provide a method for automatically collecting detailed, objective information about a person's driving performance (LeBlanc et al. 2006, 2007) and have led to a number of naturalistic driving studies (Campbell, 2012). At the same time, most have concentrated on motor vehicles, including cars, trucks, and motorcycles, and the primary focus has been on understanding safety-related behaviors rather than estimating exposure.

Thus, it is not surprising that most of the available exposure data on pedestrians and bicycles comes from sources other than naturalistic data collection (Vanparijs et al. 2015). These include various estimation models using: survey data such as the NHTS (Clifton and Krizek 2004; Salon and Handy 2014); data from pedestrian and bicyclist counts for relatively small areas and taken during one or a few points in time (Gallop et al. 2011; Griswold et al. 2011); and data for other location-specific characteristics such as employment, household size, and land use (Schneider et al. 2009).

In the limited cases in which naturalistic data have been used to examine pedestrian and/or bicycle behavior, the focus has typically not been on exposure per se but rather risk factors for collisions or crashes. Some of these studies involved the installation of unobtrusive video cameras at intersections to examine unsafe behaviors of cyclists such as red light running or helmet use (Johnson et al. 2008; Pai and Jou 2014; Wu et al. 2012). Most of the other studies involved the instrumentation of bicycles themselves; several of these latter studies are highlighted below.

Johnson et al. (2010) used helmet-mounted video cameras to capture the behaviors (head checks, reactions, maneuvers) of cyclists in Melbourne, Australia, that were associated with collisions, near collisions, and other events. Their data were limited to 127 hours and 38 minutes for 13 participants, and were not intended to generate information on exposure for this or a wider set of cyclists.

Dozza et al. (2012) described their efforts to adapt naturalistic driving methods to bicycles in Gothenburg, Netherlands, including the equipment used, data produced, tools and algorithms for visualizing and pre-processing the data, methods of analysis, and lessons learned. Results were reported for 12 participants, with data collection occurring over two weeks for each participant. The authors noted that their study complements the analyses of critical safety events by Johnson et al. (2010), by adding kinematics, location, and information about distraction by cyclists, leading to a better understanding of crash causation and providing a basis for deriving measureable safety indicators for development of intelligent countermeasures.

In related work, Werneke and Dozza (2014) used naturalistic cycling data from Gothenburg, in combination with crash, insurance, exposure, weather, road, and interview data to better understand single bicycle crashes and the factors contributing to them. According to the authors, naturalistic cycling studies can be used to fill in the gaps in reporting for single bicycle crashes and allow for the capture bicyclists' behavior before and during safety critical events, overcoming the limitation of post-crash data sources.

Building on methods used in the 100-car study conducted by the Virginia Tech Transportation Institute, Jahangiri et al. (2015) developed a smaller data acquisition system (consisting of several sensors measuring acceleration, speed, and current location) that can be used to study bicyclists' behavior and more specifically to develop bicycle violation prediction models. They also incorporated connected vehicle technology to facilitate communication within the system.

Investigators in Stockholm, Sweden, also used global positioning system logging devices and cameras to identify accessibility and safety problems among a sample of 16 commuter cyclists, as well as generate an accessible geographical interface for use as traffic planning tool (Gustafsson and Archer 2013). Specific study aims were to: identify the frequency and location of safety and accessibility/mobility problems and their causes; map and document these problems; help inform policy and strategy development; and help traffic planners better understand the problems faced by commuter cyclists on a daily basis. Participants were asked to ride 17 major cycle routes during the morning and afternoon peak traffic hours, resulting in the identification of more than 500 safety and accessibility/mobility problems.

In another naturalistic cycling study, Schleinitz et al. (2015) equipped three types of bicycles (conventional, pedelecs, and S-pedelecs) with a data acquisition system consisting of sensors to measure speed and distance, and two cameras. Using data collected from 85 cyclists over a period of 4 weeks each, the authors examined differences in speed and acceleration between bicycle types, as well effects of age and infrastructure features (e.g., bicycle lane, path, part of road used by cars, and foot path); they were not able to assess the implication of results on crash risk but speculated that higher speeds are associated with more severe crash outcomes.

A few studies used data from the naturalistic driving studies focusing on motor vehicles to examine various aspects of pedestrian/bicycle safety. For example, Lin et al. (2015) used data from the Strategic Highway Research Program 2 Naturalistic Driving Study to examine interactions between drivers and various pedestrian features at selected signalized intersections through which they drove. However, their interest was in assessing the effectiveness of selected pedestrian features in improving pedestrian safety and not estimating exposure. Other investigators used data from a 110-car naturalistic driving study in Indianapolis, Indiana, to identify potential conflict situations involving pedestrians and vehicles (Du et al. 2013; Tian et al. 2014); they concluded that this approach holds promise for studying pre-crash scenarios for vehicle to pedestrian collisions.

Collectively, the studies highlighted above suggest a promising start for applying naturalistic data collection methods to pedestrians and bicyclists to better understand safety-related problems, especially factors associated with crash and near crash risk. However, the use of naturalistic observation for these segments of the road user population is not without its challenges. For example, Dozza et al. (2012) pointed out that bicycle data loggers, unlike those used in cars or trucks, need to be small, light, waterproofed, tolerant to shocks and vibrations, low cost, and use as little energy as possible. In addition, they noted that higher drop-out rates might be expected for bicycling studies, compared to

naturalistic driving studies, due to inclement weather and more convenient alternatives to bicycling. They also cautioned that privacy may be more of a concern for participants in naturalistic cycling studies, especially when cycles are taken indoors with cameras still recording, and that data loggers on cycles are more exposed to theft and tampering, especially when left outside and unattended.

The lack of studies using naturalistic data collection for the sole purpose of estimating exposure raises concern about whether this approach is a practical approach to measure pedestrian and bicyclist exposure. It may be more fruitful to explore naturalistic observation as a tool for supplementing other approaches to estimating exposure. For example, there may be a role for naturalistic data collection in helping to calibrate or validate estimation models for exposure and provide more robust measures of risk.

Summary and Conclusions

This chapter summarized numerous examples of exposure analyses that were conducted on specific transportation facilities. The facility-specific exposure analyses were most often used to identify high-priority locations for pedestrian and bicyclist safety improvements, and were typically conducted for an entire city. In some cases, the facility-specific information was also aggregated to provide overall trends for certain road types or for subareas within a city.

Data Sources and Methods
Most of the facility-specific exposure analyses used pedestrian and bicyclist count data from one or both of these sources:
- **Direct measurement:** Many cities are now directly collecting pedestrian and bicyclist count data on an annual basis, just like motorized vehicle counts. However, these counts are collected at a very limited number of locations, and often at the locations with the most pedestrian and bicyclist volume in the city.
- **Estimation and models:** Because directly-measured counts are typically collected at a limited number of locations, various estimation and modeling methods are often used to provide count estimates for all locations within a city or other defined area. In many cases, the sample of direct counts are used in the development and calibration of these estimation models.

For direct measurement of pedestrian and bicyclist counts, much progress has been made in the past ten years. Several companies now offer automated count equipment that helps to make pedestrian and bicyclist counting more efficient and cost-effective. The NBPD provided early guidance and helped to promote count data collection. Since then, FHWA has included a chapter specifically devoted to nonmotorized traffic monitoring in their 2013 TMG, and this chapter is likely to be updated in 2017. In 2014, NCHRP Report 797 Guidebook on Pedestrian and Bicycle Volume Data Collection was published and is a comprehensive resource on pedestrian and bicycle count data collection.

For estimating pedestrian and bicyclist counts, direct demand models have been the most widely used models for facility-specific exposure estimation thus far, and typically use regression analysis to relate directly measured counts to other measured attributes of the adjacent environment (e.g., land use and form, street type, etc.). Assuming that these measured attributes are available citywide, the regression model allows one to extend the sample of facility-specific counts to all facilities citywide. This chapter provided details on other types of modeling approaches that have been used on a limited basis, or could be used for facility-specific exposure estimation. These approaches include regional travel demand

models, GIS-based models, trip generation and flow models, network analysis models, discrete choice models, and simulation-based traffic models.

Exposure Measures

Similar to the areawide exposure analyses, the units used in facility-specific exposure measures varied widely. Since the primary data source was pedestrian and bicyclist count data (rather than surveyed trip data in areawide exposure analyses), the units of exposure typically were a volume count for specified time period, or a distance traveled (calculated by multiplying a count by a street crossing width or road segment length). In a few cases where the exposure values were very high, the exposure was given in units of 1 million or 10 million (e.g., 1 million pedestrian miles traveled, 10 million pedestrian crossings).

Unlike areawide exposure analyses, several of the facility-specific exposure analyses did account for the interaction of nonmotorized and motorized traffic in their exposure measure. Several analyses computed the product of pedestrian and/or bicyclist traffic and motorized traffic ((P or B) × V) at intersections or other street crossings. A few other analyses used exposure measures like pedestrian crossings (or pedestrian miles) per entering motorized vehicle. Thus, having more granular exposure data on specific facilities does provide a better opportunity to quantify the level of interaction between pedestrian or bicyclist traffic and motorized vehicle traffic.

CHAPTER 5. RISK FACTORS OTHER THAN EXPOSURE

Understanding risk factors is an important step toward the improvement of pedestrian safety because a complete understanding can contribute to developing effective countermeasures. The discussion in this section focuses on significant factors that influence the risk of pedestrian and bicyclist crashes and crash-related injuries as identified in the literature.

Other Risk Factors

To perform the scalable estimate of exposure, two major levels are considered: disaggregate level (facility) and aggregate level (corridor, network/system, and regional). Risk factors other than exposure can also be divided based on these two levels. Figure 6 shows the flow chart of other risk factors.
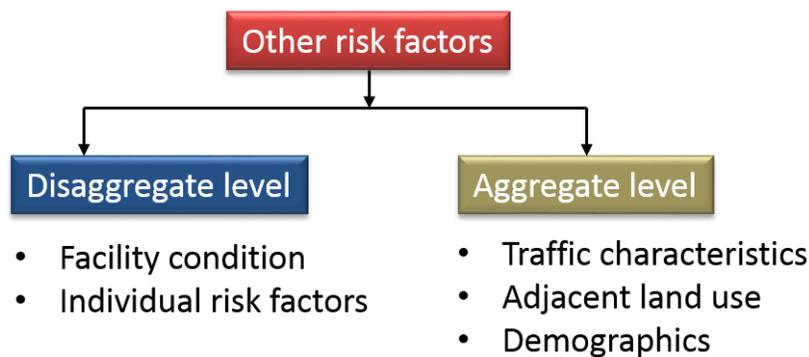
Figure 6. Division of Risk Factors Other Than Exposure for Pedestrian and Bicyclist Crashes

Understanding the exposure to risks is beneficial for safety improvement. For a systematic safety planning process, it is important to prioritize locations with an aim to reduce the crash risk and crash severity for pedestrians and bicyclists for a given countermeasure.

Disaggregate level

Disaggregate-level characteristics have significant influence on the occurrence of pedestrian and bicycle crashes. Many studies investigated the association between site characteristics and both pedestrian exposure and pedestrian crashes. The research synthesis on disaggregate-level risk factors focuses on two major issues: facility condition and individual level.

Facility Condition

Facility condition is subdivided into three major groups: (a) feature type, (b) segment, and (c) intersection. Table 8 lists the facility condition risk factors and related studies.

Table 8. List of Studies on Facility Condition

Category	Risk Factors	Studies
Feature Type	Urban/Rural	Harkey and Zeeger, 2004; DaSilva et al., 2003; Choueiri et al., 1993; Mueller et al., 1988; Litman and Fitzroy, 2009; Ewing and Dumbaugh, 2009; Ibrahim and Sayed, 2011; Tarko and Azam, 2011; Dixon et al., 2015; Kamyab et al., 2003; Jones and Carlson, 2003;
	Divided/Undivided	Obaidat et al., 2007;
	Workzone	Shaw et al., 2016;
Segment	Posted speed	Limpert, 1994; Leaf and Preusser, 1999; Litman, 2008; Peden, 2004; Renski et al., 1999; Abdel-aty and Keller, 2005;
	Lighting at night	Sze and Wong, 2007; Ulfarsson et al., 2010; Sullivan and Flannagan, 2011; Aziz et al., 2013; Hunter et al., 1996; Klop and Khattak, 1999; Johnson 1997; Abdel-aty, 2003; Haleem et al., 2015; Siddiqui et al., 2006; Das and Sun, 2015;
	Sidewalk	Knoblauch et al., 1987; Mcmahon et al., 1999;
	Bike lane	Kroll and Ramey, 1977; Conway et al., 2013;
	On street parking	Marshall et al., 2008;
	Shoulder width	Dixon et al., 2015; Klop and Khattak, 1999; Mcmahon et al., 1999;
	Number of lanes	Aziz et al. 2013; Wang et al. 2006; Poch and Mannering 1996; Spainhour and Wootton, 2007; Das and Sun, 2015;
	Bus Stop	Miranda-Morenoetal., 2011; Ukkusuri et al., 2012; Wang and Kockelman, 2013; Chen and Zhou, 2016;
Intersection	Signalization	Abdel-aty and Keller, 2005; Koepsell, 2002; Zegeer et al., 2001; Lee and Abdel-aty 2005; Oxley et al. 1997;
	Crossings	Oxley et al.,1997; Coffin and Morrall, 1995; Lassarre et al., 2007;
	Width	Zajac and Ivan, 2003;

Feature Type

Urban or Rural Roadways

The prevalence of walking and biking is greatest in urban and urbanized areas. Most non-motorized crashes occur in urban areas, where concentrations of vehicles, pedestrians, and bicyclists are higher than in rural areas. Approximately 80 percent of injury crashes and 65 percent of fatal crashes occur in urban areas due to high non-motorist activity and traffic volumes (Harkey and Zeeger, 2004; DaSilva et al., 2003). However, the ratio of fatal crashes to injury crashes is nearly three times greater in rural areas than in urban areas (Choueiri et al., 1993), which is attributed to higher speeds on rural roadways. Other studies also concluded that pedestrians in rural areas had higher rates of injuries and severe injuries than pedestrians in urban areas (Mueller et al., 1988; Litman and Fitzroy, 2009; Ewing and Dumbaugh, 2009; Ibrahim and Sayed, 2011; Tarko and Azam, 2011). There is an abundance of studies conducted on urban non-motorized crashes. Since non-motorized trips are more likely to end in a crash in an urban location, rural non-motorized crashes have been studied less often. Dixon et al. (2015) conducted a study on the non-motorized crashes on rural two-lane and multilane roadways in Texas. The findings showed that high speeds and narrow shoulders were highly associated with fatal non-motorist crashes.

These findings are in line with the findings from other studies (Kamyab et al., 2003; Jones and Carlson, 2003). Another significant variable in Jones and Carlson's (2003) study was the flow rate of heavy vehicles in the same direction as bicyclists.

Divided or Undivided Roadways

The type of median (divided or undivided) has an effect on the safety of non-motorized trips. It is most significant for intersections. It is usually easier to cross the approach on divided roads than on undivided roads since pedestrians or bicyclists have a shorter distance to cross prior to reaching a refuge area. Research has shown that divided roadways are safer than undivided roadways while crossing (Obaidat et al., 2007).

Workzone

In the United States, nearly 17 percent of work zone crashes involved a non-motorized road user in the recent years (Shaw et al., 2016). Bryden and Andrew (1999) concluded that work zone non-motorist crashes accounted for 15 percent of all serious injuries and over 40 percent of all fatalities in New York during 1993-1997. They also showed that two-thirds of the motor vehicles involved in crashes left the traffic lane and entered into the work area.

Segment

Posted Speed

Higher posted speed increases the probability of a pedestrian or bicyclist fatality. The findings of one study showed that the risk of a pedestrian crash fatality is estimated to increase from 5 percent to 45 percent when speed increases from 20 to 30 mph; the risk increases to 85 percent when speed reaches 40 mph (Limpert, 1994). Similar findings are seen in other studies (Leaf and Preusser, 1999; Litman, 2008). While pedestrians have a 90 percent chance of surviving a crash involving a vehicle traveling 20 mph or below, they have less than a 50 percent chance of surviving a crash with a vehicle traveling 30 mph or above (Peden, 2004). Many studies concluded that reduced speeds would have been effective in reducing non-motorized crashes and severities (Limpert, 1994; Leaf and Preusser, 1999; Litman, 2008; Peden, 2004; Renski et al., 1999; Abdel-Aty and Keller, 2005). The literature review on impact speed is described in a different section.

Lighting

Pedestrians and bicyclists have a higher probability of being in a fatal crash under poor lighting conditions. This finding is supported by several studies (Sze and Wong, 2007; Ulfarsson et al., 2010; Sullivan and Flannagan, 2011; Aziz et al., 2013; Hunter et al., 1996; Klop and Khattak, 1999; Abdel-Aty, 2003; Haleem et al., 2015; Das and Sun 2015). The odds of a fatal injury in daylight are reduced by 75 percent at midblock locations and 83 percent at intersections compared to dark conditions with no lighting. Street lighting reduces the same odds by 42 percent at midblock locations and 54 percent at intersections (Siddiqui et al., 2006). Klop and Khattak (1999) concluded that street lighting decreased the severity of injury compared to dark conditions in rural areas. Dark lighting conditions with no streetlights are associated with slightly higher increases in pedestrian crash severity at unsignalized intersections compared to signalized intersections (Haleem et al., 2015).

Sidewalks

Sidewalks encourage walking and improve the safety of pedestrians. Locations with no sidewalks are prone to pedestrian crashes. Knoblauch et al. (1987) determined that sites without sidewalks were more than twice as likely to be pedestrian crash prone than sites with sidewalks. The presence of a sidewalk

was found to have a particularly large safety benefit in residential and mixed residential areas. However, sidewalks seem less effective on pedestrian crashes in medium or larger commercial areas. McMahon et al. (1999) found that the likelihood of a location with a paved sidewalk being a crash site was 88.2 percent lower than a location without a sidewalk.

Bike Lane

Kroll and Ramey (1977) examined the interactions between bicyclists and drivers for a bike lane by observing an affiliated cyclist riding on 10 streets with bicycle lanes and 10 streets without bicycle lanes. The results concluded that the mean separation distance between bicycles and cars was largely a function of the motorist's available travel space (the distance between the bicyclist and the centerline) rather than the presence or absence of a bicycle lane. The results also indicated that bicycle lanes as narrow as 3 ft provided sufficient space for drivers to interact safely (Kroll and Ramey, 1977). Bicycle lane design has significant influence on bicycle crashes. Considering three types of bicycle lanes—Type 1 (a standard bicycle lane located adjacent to a travel lane and separated from the curb by vehicle parking), Type 2 (a buffered bicycle lane separated from the curb by parking and from the vehicle travel lanes by a striped buffer), and Type 3 (a curbside bicycle lane protected by parked vehicles)—Conway et al. (2013) concluded that Type 3 was safer than the other two options.

On street Parking

It is usually believed that on-street parking decreases the space for both drivers and non-motorized travelers. A study found that low-speed streets with on-street parking had the lowest fatal and severe injury non-motorized crash rates of any road category, suggesting that presence of parking had a measurable effect on vehicle speeds (Marshall et al., 2008).

Shoulder Width

One study found that an unpaved shoulder of 4 ft or more made a location 89 percent less likely to be a non-motorized crash site (McMahon et al., 1999). This finding is in line with the findings of Dixon et al. (2015). Another study concluded that shoulder width of any size was not statistically significant on crash severity compared to the absence of a shoulder (Klop and Khattak, 1999).

Number of Lanes

The number of lanes on a road is a significant factor on the severity level of non-motorized crashes. Results from one study indicated that crashes on single-lane roads had a lower probability of resulting in a fatality. Moreover, results showed that crashes on multilane roads had a higher probability of resulting in a fatality (Aziz et al., 2013). This finding is consistent with the results of previous studies (Wang et al., 2006; Poch and Mannering, 1996; Das and Sun, 2015). One study concluded that the higher the number of lanes that a pedestrian tried to cross before being hit, the more likely it was that the pedestrian was at fault (Spainhour and Wootton, 2007), partially because of the higher amount of exposure time while crossing.

Bus Stops

Several studies showed that the presence of bus stops on roadway segments is closely associated with higher non-motorist crash frequency (Miranda-Moreno et al., 2011; Ukkusuri et al., 2012; Wang and Kockelman, 2013; Chen and Zhou, 2016). Bus stops usually generate more non-motorist activities, and failure to provide clear distance for the non-motorists causes a higher number of crashes.

Intersection

Statistics suggest that crossing the street at the intersection is more risky than walking or biking along the roadways. The reason is that pedestrian exposure is higher while crossing than the walking or biking along the roadway. Intersections without traffic control signals and absence of cross walks are found to be highly correlated with fatal non-motorized crashes (Sze and Wong, 2007; Moudon, 2011). Another important factor in this regard is the crossing behavior of the non-motorized traveler. One study found that fatal crashes are strongly associated with pedestrians crossing un-signalized intersections and vehicles moving straight ahead on a roadway (Ulfarsson et al., 2010; Moudon, 2011).

Signalized and Unsignalized Intersection
A study investigating the crash severities at signalized intersections found that crashes involving a pedestrian or a bicyclist and a motor vehicle turning left had a high probability of resulting in severe pedestrian or bicyclist injury (Abdel-Aty and Keller, 2005). For pedestrians on state routes, the most dangerous action to take was to cross these routes at unsignalized intersections, where the likelihood of being involved in a fatal or severe injury crash was approximately four times that of being anywhere else on the route. This finding supported previous research and suggested that engineering approaches to road design could improve the safety of pedestrians (Koepsell, 2002; Zegeer et al., 2001). Lee and Abdel-Aty (2005) noted that drivers tended to drive more carefully when they approached traffic signals than stop or yield signs in rural areas and pedestrian crashes occurred less frequently at rural signalized intersections.

Crossings
Crosswalk characteristics have been associated with severity of injury. For example, one study found that on a two-lane road, crash severity did not differ significantly for crashes occurring at marked and unmarked crosswalks, but on multilane roads, there was evidence of more fatal crashes at marked crosswalks compared to unmarked crosswalks (Zegeer et al., 2001). Additional analysis of the data revealed that the ADT level along with the presence of other traffic control devices was key to explaining the relationship. Another study showed that over 40 percent of pedestrian fatalities occurred in locations without crosswalks (Ernst, 2004). Several studies examined crossing behavior and identified behaviors with greater risk for different age groups; for example, older people's slower gait increases the time spent crossing a road, thereby increasing exposure (Oxley et al., 1997; Coffin and Morrall, 1995; Lassarre et al., 2007).

Individual Level
Individual level of behavior is one of the most dominant factors in pedestrian and bicyclist crashes. Risk factors associated with the individual level are subdivided into four major groups: (a) vehicle related, (b) bicycle related, (c) driver related, and (d) pedestrian/bicyclist related. Table 9 lists the studies focusing on the individual-level risk factors.

Table 9. List of Studies on Individual Level Risk Factors

Category	Risk Factors	Studies
Vehicle related	Impact speed	Rosen et al., 2011; Tefft, 2011;
	Vehicle age	Peden, 2004; Blows, 2003;
	Vehicle size	Galloway and Patel, 1982; Atkins et al.,1988; Mizuno and Kajzer, 1999;
Driver	Age	Lee and Abdel-Aty, 2005
	Distraction	Dimaggio and Durkin, 2002
	Gender	Das and Sun, 2015
	Occupants	Das and Sun, 2015
Pedestrian / bicyclist	Age	Assailly 1997; Davies 1999; Vyrostek et al. 2001; Retting et al. 2003; Gawryszewski and Rodrigues 2006; WHO 2009; Ponnaluri and Nagar 2010; Green et al. 2011; Hurruff et al. 1998; Fontaine and Gourlet 1997; Rodgers 1995;
	Child pedestrian	Davies, 1999; USDOT, 2001; NCIPC, 2006; Connelly et al., 1998; Whitebread, 2000; Agran et al., 1994; Wills et al., 1997; Macpherson et al., 1998; Howard et al., 2005; King and Palmisano, 1992; Laflame, 2000; Lascala et al., 2000; Rivara and Barber, 1986; Carlin et al., 1995; Wazana, et al. 2000;
	Gender	Campbell, 2004; NCSA, 2008; Li and Baker, 1994; NHTSA, 2011;
	Intoxication	Lee and Abdel-Aty, 2005; Oxley et al., 2006; Spainhour et al., 2006; Clayton and Colgan, 2001; Miles-Doan, 1996; Öström and Eriksson, 2001; Holubowycz, 1995; Leaf et al., 2005;
	Reflective clothing	Luoma and Trauba, 1995; Owen and Sival, 1993; Tyrrell and Patton, 1998; Tyrrell et al., 2004a; Tyrrell et al., 2004b;
	Cell phone	Hatfield, 2007; Hyman et al., 2010; Nasar et al., 2008; Stavrinos et al., 2011;
	Crossing behavior	Palamarthy et al., 1994; Quddus et al., 1996; Hunter and Huang, 1995;
	Temporal effect	Harkey and Zeeger, 2004; Hunter and Huang, 1995;

Vehicle related

Impact Speed

It is well established that the risk of a severe or fatal non-motorized crash is significantly associated with the impact speed (Rosén et al., 2011). Rosén et al. (2011) reviewed a substantial number of studies on the relationship between crash impact speed and pedestrian fatality risk published prior to 2010. Of the 11 studies considered for analysis, five were based on data collected prior to 1980 (including three different studies of the same data), and nine were biased due to overrepresentation of crashes. At lower speeds (like 15 mph or below), risks were low and the trend of increment was smaller with small increments in speed. At impact speeds below 15 mph, pedestrians (about 91 percent) did not endure severe injuries, and very few (about 2–5 percent) were killed. However, as speeds increased beyond this lower speed range, small changes in speed yielded a relatively larger increment in risk. At an impact speed of 25 mph, an estimated 30 percent of pedestrians sustained a severe injury, and about 12 percent were killed. Approximately half of all pedestrians (47 percent) struck at 30 mph sustained severe injury, and one in five (20 percent) died. Risks for a pedestrian struck at any given speed by a light truck were higher than if struck at the same speed by a car. Risks were higher for an older pedestrian struck at any given speed than for a younger pedestrian struck at the same speed (Tefft, 2011).

Vehicle Age
The association between vehicle age and risk of non-motorized crashes has been investigated in a few studies (e.g., Peden, 2004; Blows, 2003). These studies quantify the increased risk of car crash injury associated with older vehicle year.

Vehicle Size
Some studies observed that larger cars resulted in more serious pedestrian injuries (Galloway and Patel, 1982; Atkins et al., 1988) and higher pedestrian fatality rates (Mizuno and Kajzer, 1999). The larger vehicles were related with more traumatic brain, thoracic, and abdominal injuries. At higher speeds, there was no association with size of vehicles. The study suggested that the occurrence of these injuries is independent of vehicle type for certain threshold speeds. Compared to conventional cars, pedestrians hit by sport utility vehicles and pick-up trucks were more likely (with odds of 1.48) to have higher injury severity or be killed, with odds of 1.72 (Mizuno and Kajzer, 1999).

Driver related

Driver Age
One study showed that middle-age (25–64) and male drivers are more prone to be involved in non-motorist crashes (Lee and Abdel-Aty, 2005).

Driver Distraction
One study concluded that driver distraction and associated situational factors increase the probability of non-motorized crashes (Dimaggio and Durkin, 2002).

Driver Gender
Das and Sun (2015) found that male drivers have a greater association with severe and moderate injury pedestrian crashes. The study also showed that female drivers are associated with a higher number of pedestrian crashes during inclement weather.

Number of Occupants
Das and Sun (2015) found that drivers with multiple passengers are associated with a higher number of pedestrian crashes.

Pedestrian/Bicyclist Related

Age
Age is a significant personal-level factor in non-motorized crashes. Children are particularly at risk in road traffic crashes (Assailly, 1997; Davies, 1999; Vyrostek et al., 2001; Retting et al., 2003; Gawryszewski and Rodrigues, 2006; WHO, 2009; Ponnaluri and Nagar, 2010). Many researchers focused on child pedestrians in their investigations (e.g., Green et al., 2011). Harruff et al. (1998) performed a retrospective analysis of 217 pedestrian traffic fatalities in Seattle, Washington. The study concluded that elderly pedestrians were most vulnerable because they are more likely to be injured as a pedestrian and are more likely to die because of their vulnerabilities. Fontaine and Gourlet (1997) concluded that younger and older pedestrians showed more exposure risk than other age groups. Rodgers (1995) determined that bicyclists over 65 years old were significantly more likely to be in fatal crashes than bicyclists from other age groups.

Child Pedestrian

A range of demographic factors is associated with child pedestrian risk, such as the age of the child. Epidemiological influences of age are predominant among these factors. Studies showed that middle childhood is a time of increased risk for child pedestrian injury (Assailly, 1997; USDOT, 2001; NCIPC, 2006). As children grow older, between the ages of 5 and 9, their pedestrian skills gradually increase (Connelly et al., 1998; Whitebread and Neilson, 2000). Some studies showed that children wandering farther from home while unsupervised accounts for the increase in the injury rate (Agran et al., 1994; Wills et al., 1997; Macpherson et al., 1998). Children from an ethnic minority background are at higher risk for pedestrian injury (Howard et al., 2005; King and Palmisano, 1992; Laflamme, 2000; LaScala et al., 2000). This finding may be due to their homes typically being located in urban areas with greater traffic density and higher rates of unemployment. Pedestrian injury rates are higher in low socioeconomic status urban areas with higher traffic density, denser housing units, and fewer safe areas for children to play (Laflamme, 2000; Rivara and Barber, 1986). Exposure time studies showed increased injury rate odds of 2.2 for children riding bicycles for more than 3 hours per week compared to children riding less than 1 hour. Riding more than 5 km on the sidewalk was also associated with increased injury risk, with odds of 3.1 (Carlin et al., 1995). One study concluded that child pedestrian injury rates are 2.5 times higher on one-way than on two-way streets (Wazana et al., 2000).

Gender

The behavior and actions of pedestrians significantly affect a crash outcome. Research suggests that males have a higher probability than females to be killed in a crash. Males showing higher risk behaviors than females (Campbell, 2004) explains why more males than females die as the outcome of a non-motorized crash. In 2000, the fatality rate of male pedestrians was twice that of female pedestrians (National Center for Statistics and Analysis [NCSA], 2008) in the United States. Based on daily trips, men were found to be at a slightly lower injury risk than women (Li and Baker, 1994). Recent National Highway Traffic Safety Administration (NHTSA, 2011) data show that in 2009, 549 male bicyclists were killed and another 41,000 were injured. This was compared to 81 female bicyclist fatalities and 10,000 injuries. For child pedestrians, gender is also associated with risk for injury (Assailly, 1997; Howard et al., 2005), with boys experiencing injury at a rate roughly double that of girls (NCIPC, 2006).

Intoxication

 Research suggests that intoxicated pedestrians are at significantly higher risk of injury (Clayton and Colgan, 2001). Moreover, as a non-motorist's blood alcohol concentration (BAC) increases, the probability of that non-motorist being involved in a fatal crash increases. Non-motorists under the influence of alcohol have also been shown to exhibit risky road-crossing behaviors (Lee and Abdel-Aty, 2005; Oxley et al., 2006; Spainhour et al., 2006). One study found that 43 percent of male pedestrians and 21 percent of female pedestrians involved in fatal crashes had BACs at or above .08 g/dL (Leaf et al., 2005). Miles-Doan (1996) showed that impaired pedestrians were more involved in crashes and their odds of dying compared to surviving were higher. Ostrom and Eriksson (2001) found that impaired pedestrians were more severely injured and suffered more head injuries. Some studies considered the mixed effect of several factors like pedestrian age, gender, and alcohol use on the risk outcomes. For example, Holubowycz (1995) reported that young and middle-age intoxicated males were high-risk non-motorist groups.

Reflective Clothing

Several studies established that wearing retroreflective materials increased recognition distance (Luoma et al., 1995; Owen and Sivak, 1993). Research shows that pedestrians usually overestimate their own

visibility to drivers and underestimate the benefits of retro-reflective materials in dark conditions (Tyrell and Patton, 1998; Tyrell et al., 2004a; Tyrell et al., 2004b).

Cell Phone
Research has found that improper situational awareness and distracted attention levels are significant factors among pedestrians using mobile phones (Hatfield and Murphy, 2007; Hyman et al., 2010; Nasar et al., 2008; Stavrinos, 2011). Field studies (Hatfield and Murphy, 2007; Nasar et al., 2008) observed that pedestrians made more unsafe street crossings when conversing on a cell phone than when undistracted.

Crossing Behavior
Palamarthy et al. (1994) conducted a detailed study on the crossing behavior of pedestrians. Findings showed that 18 percent crossed during a no-walking signal and only 9 percent waited for the next steady walking signal. This type of behavior is associated with a higher number of pedestrian and bicycle crashes (Abdulsattar, 1996). A study by Hunter and Huang (1995) concluded that the most common bicyclist crash contributing factors were failure to yield (represented 21 percent of crashes), stop sign violations (represented 7.8 percent of crashes), and safe movement violations (represented 6.1 percent of crashes). The condition of the bicycle was found to be without defects in 91 percent of cases.

Temporal Effect
A study by Campbell (2004) showed that the highest proportion of pedestrian crashes happened between 3 p.m. and 6 p.m. Most pedestrian fatalities tend to occur at night (Campbell, 2004; Harkey and Zeeger, 2004). Significant numbers of older pedestrian crashes occurred in fall and winter months, whereas younger pedestrian crashes occurred significantly during the spring and summer months (Campbell, 2004). Harkey and Zeeger (2004) determined higher clustering of pedestrian fatalities on weekend days. Hunter and Huang (1995) showed that more crashes involving a bicyclist occur during the fair-weather months of April to October and on weekdays.

Aggregate Level

Many studies used larger spatial units (like U.S. census county, tract, block group, and block) to determine the key association factors in pedestrian and bicycle crashes. This level is divided into three groups: (a) traffic characteristics, (b) land use characteristics, and (c) demographics.

Traffic Characteristics
Traffic characteristics like traffic volume and non-motorist volume are closely associated with non-motorist crash risks. Roadways with higher traffic and non-motorist traffic increase risk exposures significantly. Table 10 lists the studies on traffic characteristics.

Table 10. List of Studies on Traffic Characteristics

Category	Risk Factors	Studies
Traffic volume	AADT	Garder, 2004; Lee and Abdel-Aty, 2005; Loukaitou-Sideris et al., 2007; Wier et al., 2009; Cottrill and Thakuriah, 2010; Siddiqui and Abdel-Aty, 2012; Abdel-Aty et al., 2013;
	Walk and bike trips	Dixon et al., 2015;
	Percentage of trucks	Retting, 1993;

Traffic Volume Related

AADT
Research suggests that crash risk from a pedestrian's perspective is more influenced by pedestrian volume than vehicle volume (Garder, 2004). In many places, it is problematic to determine pedestrian or bicyclist volume of different age groups at intersections or roadway segments. Thus, it is difficult to determine what proportion of the pedestrians were actually involved in crashes. Frequency of pedestrian crashes usually increases with traffic volume up to a certain threshold. This indicates that pedestrian or bicycle crashes are more likely to occur at intersections or segments with higher traffic volume since higher volume increases the potential conflict points between non-motorists and vehicles. However, it appears that the rate of increase gradually decreases as traffic volume increases after certain thresholds for different roadway classes (Lee and Abdel-Aty, 2005; Loukaitou-Sideris et al., 2007; Wier et al., 2009; Cottrill and Thakuriah, 2010; Siddiqui and Abdel-Aty, 2012; Abdel-Aty et al., 2013).

Walk and Bike Trips
Dixon et al. (2015) conducted research to evaluate the relationship between non-motorized trips and risk outcomes on rural two-lane and multi-lane roadways. The relationship between higher non-motorized trips and crash severity outcomes was not significant at 95 percent confidence interval.

Percentage of Trucks
One study found that pedestrian fatalities involving large trucks were more likely to occur at intersections. Results also showed that large truck fatal crashes involved pedestrians aged 60 or above, and other vehicle fatal crashes involved pedestrians aged 40 and above (Retting, 1993). The two most common crash scenarios, representing 47 percent of all crashes, involved large trucks proceeding forward either at intersections or segment locations. Trucks turning and striking pedestrians with the front of the trucks, the rear wheels, or the trailers accounted for another 24 percent, and trucks backing up fatally injured pedestrians in 10 percent of cases (Retting, 1993).

Land Use Characteristics

A wide selection of spatial units has been examined in macro-level crash modeling for non-motorized trips in the safety literature. This includes block group (Levine et al., 1995), TAZ (Abdel-Aty et al., 2011; Guevara et al., 2004; Hadayeghi et al., 2003; Hadayeghi et al., 2006; Hadayeghi et al., 2010; Ng et al., 2002; Washington et al., 2010; Naderan and Shahi, 2010), census wards (Noland and Quddus, 2004a; Quddus, 2008), standard statistical regions (Noland and Quddus, 2004b), census tract (Lascala et al., 2000; Quddus, 2008; Loukaitou-Sideris et al., 2007; Wier et al., 2009; Cottrill and Thakuriah, 2010;

Ukkusuri et al., 2011), county (Aguero-Valverde and Jovanis, 2006; Amonros et al., 2003; Huang et al., 2010; Karlaftis and Tarko, 1998; Noland and Oh, 2004), state (Noland, 2003), local health areas (Macnab, 2002), and grid-based structure (Kim et al., 2006). Table 11 lists the studies associated with land use characteristics.

Table 11. List of Studies on Adjacent Land Use

Category	Risk Factors	Studies
Land use	Socio-economic	Lascala, 2000; Wier et al., 2009; Qin and Ivan, 2001;
	Crime	Bagley, 1992; Cottrill and Thakuriah, 2010; Green et al., 2011;
	Ethnicity	Rivara and Barber, 1986; Agran et al., 1998; Hilton, 2006; Sciortino et al., 2005;
	Income	Mueller et al., 1988; LaScala, 2000; Noland and Quddus, 2004; Wier et al., 2009; Agran et al., 1998; Chakravarthy et al., 2010; Roberts et al., 1995; Delmelle et al., 2012; Graham and Glaister, 2003; Green et al., 2011; Cottrill and Thakuriah, 2010; Siddiqui and Abdel-Aty, 2012; Abdel-Aty et al., 2013
	Neighborhood	Campbell, 2004; Noland and Quddus, 2004; Clifton and Kreamer-Fults, 2007;
	Households	Mcmahon et al., 1999; Zajac and Ivan, 2003;
	Area	Qin and Ivan, 2001;
	Public schools	Clifton and Kreamer-Fults, 2007;

Socioeconomic Structure
Two studies using data from San Francisco found a relationship between socioeconomic structure and pedestrian crash severities of all ages (LaScala, 2000; Wier et al., 2009). Qin and Ivan (2001) concluded that a large number of studies recognized the indirect relationship between pedestrian crashes and socioeconomic factors.

Crime
Bagley (1992) investigated the probability of sites being hazardous given socioeconomic and crime data. Pedestrian injuries are more dominant in areas with high measures of social disadvantage, such as crime and domestic violence (Cottrill and Thakuriah, 2010; Green et al., 2011).

Ethnicity
Past studies noted a relationship between economic and ethnic differences with pedestrian crash rates. Low income and household crowding are factors associated with greater pedestrian injuries (Rivara and Barbar, 1986). Other studies have linked poverty and the lack of English language fluency with pedestrian injuries (Agran et al., 1998). The 2006 national data showed that minorities of almost all age groups were more likely to be involved in a fatal non-motorist crash than the non- Hispanic white population (Hilton et al., 2006). Underreporting of pedestrian injuries among minorities is also cited in the literature and would likely increase the amount of vulnerabilities in certain ethnicities (Sciortino et al., 2005; Abdel-Aty et al., 2013).

Income
In the U.S., children from families with low income are seven times more likely to be injured than children from families with high income (Mueller et al. 1988). Chakravarthy et al. (2010) found that the percentage of the population living in low-income households was the strongest predictor of pedestrian injuries, with pedestrian crashes four times more likely in poor neighborhoods. This finding is repeated

in a study that found that the risk of injury for children in the lowest socioeconomic stratum is more than twice that of children in higher socioeconomic categories (Roberts et al., 1995). These results are consistent with previous research that looked at pedestrian injury crashes on a smaller geographic scale (LaScala et al., 2000; Noland and Quddus, 2004a; Wier et al., 2009; Agran et al., 1998; Cottrill and Thakuriah, 2010; Green et al., 2011; Cottrill and Thakuriah, 2010; Siddiqui and Abdel-Aty, 2012; Abdel-Aty et al., 2013). Minority populations were found to have a higher incidence of non-motorist fatalities. It relates to geometric factors associated with lower-income areas, such as high-speed roads. Graham and Glaister (2003) found evidence to support this among patterns of childhood pedestrian fatalities, which are strongly associated with more poor income areas. However, a study conducted by Delmelle et al. (2012) in Buffalo, New York, found minimal effect of income on pedestrian crashes. This study showed that bicycle and pedestrian crashes were related to factors like ethnicity, educational status, and land use.

Neighborhood
A study by Epperson (1995) recognized that the economic status of a neighborhood was significantly related to the number of pedestrian crashes. The characteristics of the area or the neighborhood had significant contributions as well. Severity of pedestrian crashes was found to be higher outside of urban zones in another study (Campbell, 2004). In standard statistical regions of the U.K., lower-income areas and increased per capita expenditure on alcohol were associated with severe or fatal pedestrian crashes (Noland and Quddus, 2004).

Households
McMahon et al. (1999) studied land use variables such as the percentage of single parents with children, percentage of housing stock built after 1980, percentage of households composed of families, and percentage of the unemployment rate. The study showed that the percentage of single parents with children and percentage of housing stock built after 1980 were significantly related to segment-related pedestrian crashes. Some specific areas (for example, downtown, compact residential, low-density commercial, and medium-density commercial areas) are more likely to experience lower pedestrian crash severity than other areas, like villages or low-density residential areas (Zijac and Ivan, 2003).

Area Type
Research shows that area type is significantly related to non-motorized crashes. Because campus areas as well as tourist zones have the greatest positive effect on pedestrian exposure, Qin and Ivan (2001) argued that these zones deserve additional consideration for improvements in pedestrian facilities, such as warning devices, speed limits, stop signs, and marked crosswalks.

Public Schools
Clifton and Kreamer-Fults (2007) showed that the presence of a driveway or turning bay at a school entrance decreased non-motorist crashes and injury severity. On the other hand, the presence of recreational facilities near public schools was positively associated with a higher number of non-motorist crashes.

Demographics

Demographics influence risk intensity of non-motorists. Since land use, socio-economic status, and demographics are closely associated, this study used three broad groups as risk factors associated with demographics. These factors are: (a) population density, (b) number of licensed drivers, and (c) vehicle ownership. Table 12 lists the studies associated with demographics.

Table 12. List of Studies on Demographics

Category	Risk Factors	Studies
Demographics	Population density	LaScala, 2000; Loukaitou-Sideris et al., 2007; Chakravarthy et al., 2010; Siddiqui and Abdel-Aty, 2012; Abdel-aty et al., 2013; Graham and Glaister, 2003; Greene-Roesel et al., 2007; Miranda-Moreno, 2011;
	Number of licensed drivers	DaSilva et al., 2003;
	Vehicle ownership	Qin and Ivan, 2001;

Population Density

Many studies considered population density as a contributing factor (LaScala, 2000; Loukaitou-Sideris et al., 2007; Chakravarthy et al., 2010; Siddiqui and Abdel-Aty, 2012; Abdel-Aty et al., 2013). However, some studies showed that pedestrian safety analyses based on population density might distort the true risk values. The population variable captures the inherent likelihood of non-motorized crashes due to greater risk from pedestrian-vehicle interactions. At intersections, risk exposure has been found to be a function of pedestrian activity and traffic volume (Greene-Roesel et al., 2007; Miranda-Moreno et al., 2011). In many cases, data on pedestrian volume were not achievable and total population was used as proxy of exposure. LaScala et al. (2000) conducted a spatial regression analysis of pedestrian injuries associated with motor vehicles in San Francisco. The results showed that pedestrian injuries were associated with increased traffic flow and population density (as measured per kilometer of road length). Areas with higher unemployment were associated with higher injury rates, whereas areas with more high school graduates had lower injury rates. This finding is similar to the results of Graham and Glaister (2003), who used an areawide deprivation score in their study. This research found that larger numbers of children (ages 0 to 15) in an area were associated with fewer pedestrian injuries, contrary to the findings of other studies.

Number of Licensed Drivers

A study by DaSilva (2003) reported that there were about 0.38 drivers involved in pedestrian crashes per 1,000 licensed drivers. Younger drivers (20 years or less) held the highest probability of being involved in a crash with pedestrians, at over 0.8 drivers per 1,000 licensed drivers. The second-highest involvement rate based on the licensed driver population is associated with older drivers (85 years or more), showing nearly six drivers involved in crashes per 10,000 licensed drivers.

Vehicle Ownership

It is evident that the vehicle-owner ratio is higher in rural areas. These areas have different demographic factors, such as neighborhood environment, household median income, and unemployment, compared to urban environments. Thus, Qin and Ivan's (2001) study suggested the necessity of considering an urban setting and rural setting separately.

Proxy variables, Exposure, and Pedestrian/Bicyclist Crashes

This chapter provides a summarized view on the studies focusing on pedestrian and bicyclist risk factors other than exposure. Interested reader can consult other studies providing systematic synthesis on

pedestrian and bicyclist risk factors (Karsch et al., 2012; PEDSAFE, 2013; BIKESAFE, 2014;). It is important to note that NCHRP Report 803 described most of these risk factors (for example, population density, employment density, transit stop density, presence of sidewalk, socioeconomic characteristics) as demand proxy variables (Lagerwey et al., 2015). Moreover, findings from most of these studies indicate association, not causation, between these risk factors and crash outcomes. In many of these studies described in this chapter, risk factors were associated with pedestrian/bicyclist crashes without considering exposure into account. There is a small body of research literature that examined the link between pedestrian/bicyclist injury counts and both vehicle and pedestrian/bicycle flows at intersection locations. Zegeer et al. (1985) conducted study on pedestrian crashes at 1,297 signalized intersections in 15 cities. The findings showed that the volume of pedestrians crossing at an intersection was the most influential variable in explaining the variation in pedestrian crashes. This study also showed that vehicle volume was the second most important factor in explaining pedestrian crashes. Similar findings were found in other studies (Brude and Larsson, 1993; Lyon and Persaud, 2002; Zegeer et al., 2005;). Leden (2002) compared pedestrian crashes associated with left-turning traffic with pedestrian crashes with right-turning traffic. The results showed that left-turn volume was highly associated with a larger increase in pedestrian crashes compared to right-turn volume. Schneider et al. (2011) used vehicle and pedestrian volume data from 81 intersections. The results from negative binomial regression model showed that significantly more pedestrian crashes occurred at intersections with more right-turn-only lanes, more nonresidential driveways within 50 ft, more commercial properties within 0.1 mi, and a greater percentage of younger (< 18 years old) residents within 0.25 mi. Miranda-Moreno et al. (2011) used disaggregate vehicle and cyclist flows to develop cyclist injury frequency models. The findings showed that a 10% increase in bicycle flow was associated with a 4.4% increase in the frequency of cyclist injuries and a 10% increase in vehicle flow would result in a 3.4% increase in cyclist injury occurrence.

Summary and Conclusions

This chapter summarizes the state-of-the-art research synthesis on pedestrian and bicyclist risk factors other than exposure. The risk factors are explained based on two large categories: a) disaggregate level risk factors, and b) aggregate level risk factors. Table 13 and Table 14 show influence of the risk factors of non-motorist crashes by using selected number of major studies. An upper arrow (⇑) sign indicates that the corresponding factor is associated with higher number of non-motorized crashes and a down arrow (⇓) sign indicates that the factor is negatively associated with non-motorized crash frequencies.

Disaggregate Level
Disaggregate-level risk factors mainly associate facility condition and individual level. Facility condition considers risk factors associated with feature type (e.g., urban/rural, divided/undivided), segment, and intersection. Non-motorized trips are more likely to end in a crash in an urban location, but the ratio of fatal crash to injury crash is higher in rural locations. Many studies showed that posted higher speeds on roadway segments are closely associated with higher pedestrian and bicyclist crashes. Moreover, no lighting at dark, absence of sidewalks or bike lanes, and presence of bus stops are significant risk factors for roadway segments. On intersections, the key risk factors are wider crossings and unsignalized conditions. The individual level indicates risk factors involved with an individual unit or person. The significant risk factors are characteristics of drivers (e.g., age, distraction), characteristics of pedestrians/bicyclists (e.g., age, impairment, cell phone use), and properties of vehicles/bicycles (e.g., speed, lighting). These factors can contribute to determining direct measures of crash involvement and crash severity. For example, an intersection with a wider crosswalk is a crash-prone location for older pedestrians. This finding may be attributed to both exposure time and direct measurement of crashes.

For safety improvement, the reduction of the length of crosswalks is helpful because it decreases the exposure time that an older pedestrian needs to cross the road.

Aggregate Level

Many studies examined a wide selection of spatial units in aggregate-level analyses. This includes census block, block group, tract, county, state, TAZ standard statistical regions, and grid-based structure. In this research synthesis, aggregate-level risk factors are divided into three properties: traffic condition, land use characteristics, and demographics. Traffic condition involves risk factors like motorized and non-motorized traffic volume for different spatial units. Risk factors associated with land use characteristics involve income level, household size, percentage of minorities, etc. Many studies showed that specific socioeconomic structures (e.g., poor neighborhood, higher density of minority households) are closely associated with higher crash risks for non-motorists. Demographics include broader spatial characteristics like population density, number of licensed drivers, etc. Analyzing risk factors at the aggregate level usually directs the focus toward a systematic safety investigation. For example, a higher number of public schools in a census block group is likely to increase crashes or crash severities. To improve safety for a larger spatial unit, the authority needs to consider a wider variety of countermeasures in determining a systematic approach to safety.

Table 13. Impact of the Risk Factors at Disaggregate Level

Variables	Abdel-Aty and Keller, 2005	Aziz et al., 2013	Conway et al., 2013	Das and Sun, 2015;	Dixon et al., 2015	Howard et al. 2005	Knoblauch et al., 1987	LaScala et al., 2000	Leaf et al., 2005	Lee and Abdel-Aty, 2005	Mcmahon et al., 1999;	Nasar et al., 2008	Peden, 2004	Ponnaluri and Nagar, 2010	Retting et al., 2003	Shaw et al., 2016	Spainhour and Wootton, 2007	Tefft, 2011	Tyrrell et al., 2004	Zegeer et al., 2001
Facility Condition																				
Urban roadways	-	⇑	-	-	⇑	-	-	-	-	-	⇑	-	-	-	-	-	-	-		
Work zone	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	⇑	-	-	-
Roadway Segment																				
Higher speed	⇑	-	-	-	-	-	-	-	-	-	-	-	⇑	-	-	-	-	-	-	-
No lighting at night	-	⇑	-	⇑	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
No sidewalks	-	-	⇑	-	-	-	⇑	-	-	-	⇑	-	-	-	-	-	-	-	-	-
No Bike Lanes	-	-	⇑	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Narrow shoulders	-	-	-	-	⇑	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Number of lanes	-	⇑	-	⇑	-	-	-	-	-	-	-	-	-	-	-	-	⇑	-	-	-
Intersection																				
Unsignalized	⇑	-	-	-	-	-	-	-	-	⇑	-	-	-	-	-	-	-	-	-	⇑
Wider crosswalks	-	-	-	-	-	-	⇑	-	-	-	⇑	-	-	-	-	-	-	-	-	⇑
Vehicle																				
Impact speed	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	⇑	-
Older vehicles	-	-	-	-	-	-	-	-	-	-	-	-	⇑	-	-	-	-	-	-	-
Driver																				
Age	-	-	-	-	-	-	-	-	-	⇓	-	-	-	-	-	-	-	-	-	-
Number of occupants	-	-	-	⇑	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Non-motorist																				
Age	-	-	-	-	-	-	-	-	-	-	-	-	-	⇓	⇓	-	-	-	-	-
Child pedestrian	-	-	-	-	-	⇑	-	⇑	-	-	-	-	-	-	-	-	-	-	-	-
Intoxication	-	-	-	-	-	-	-	-	⇑	⇑	-	-	-	-	-	-	-	-	-	-
No retro-reflective wearing	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	⇑	-
Cell phone	-	-	-	-	-	-	-	-	-	-	-	⇑	-	-	-	-	-	-	-	-

Notes: ⇑ : Increase in risk, ⇓ : Decrease in risk, - : Not considered

Table 14. Impact of the Risk Factors at Aggregate Level

Variables	Abdel-Aty et al., 2013	Chakravarthy 2011	Cottrill and Thakuriah, 2010	DaSilva et al., 2003	Dixon et al., 2015	Green et al. (2011)	LaScala et al., 2000	Loukaitou-Sideris et al., 2007	Noland and Quddus, 2004	Retting, 1993	Siddiqui and Abdel-Aty, 2012	Ukkusuri et al., 2011	Wier et al., 2009
Traffic and Transportation													
Traffic Volume	⇑	-	⇑	-	-	-	⇑	⇑	-	-	⇑	-	⇑
Walk and bike trips	-	-	-	-	⇑	-	-	-	-	-	-	-	-
Percentage of trucks	-	-	-	-	-	-	-	-	-	⇑	-	-	-
Land use													
Crime	-	-	⇑	-	-	⇑	-	-	-	-	-	-	-
Low income	⇑	⇑	⇑	-	-	-	-	-	-	-	⇑	-	⇑
Minority	⇑	-	-	-	-	⇑	-	⇑	-	-	⇑	⇑	-
Non-English speaker	-	⇑	-	-	-	-	-	-	-	-	-	-	-
Alcohol Availability	-	-	-	-	-	-	⇑	-	⇑	-	-	-	-
Housing density	⇑	-	-	-	-	-	-	-	-	-	⇑	-	-
Public Schools	-	-	⇑	-	-	-	-	-	-	-	-	⇑	-
Demographics													
Population density	⇑	⇑	⇑	-	-	-	⇑	⇑	⇑	-	⇑	⇑	-
Number of licensed drivers	-	-	-	⇑	-	-	-	-	-	-	-	-	-

Notes: ⇑ : Increase in risk, ⇓ : Decrease in risk, - : Not considered

CHAPTER 6. CONCLUSIONS

The project team reviewed over 280 research reports, journal articles, and other technical documents on risk and exposure, and in particular, pedestrian and bicyclist risk and exposure. The findings of this review were summarized in Chapters 2 through 5:

- **Chapter 2** summarized **foundational definitions and concepts** for risk and exposure in the context of pedestrian and bicyclist safety analysis.
- **Chapter 3** summarized the use of **exposure measures at areawide levels** (i.e., network/system and regional), and described the data sources and methods that could be used for exposure measures at these more aggregate analysis levels.
- **Chapter 4** summarized the use of **exposure measures on specific transportation facilities** (i.e., street crossings and segments), and described the data sources and methods that could be used for exposure measures at these more granular analysis levels.
- Finally, **Chapter 5** summarized the wide variety of **risk factors (other than exposure)** that can affect pedestrian and bicyclist safety.

This chapter provides overall conclusions based on the findings summarized in the previous chapters.

Importance of Geographic Scale in Exposure Analysis

Chapter 2 noted the importance of geographic scale in estimating exposure. In this report, exposure scale was defined as the most granular geographic level for which an exposure measure is desired. For example, is an exposure measure sought for a selected number of individual street crossings? Is an exposure measure sought for certain roadway segments? Or is an exposure measure sought for a defined areawide geography, such as TAZs, Census tracts, or Census block groups?

The exposure scale will likely influence how the theoretical definition of exposure can be operationalized in a practical way, since exposure data cannot be collected on all pedestrian, bicyclist, and motor vehicle movements at all locations at all times. Therefore, the exposure scale will determine what data source and methods are practical and feasible, and what exposure measures can be readily estimated or calculated from these data sources and methods.

Future methodological development in this project could benefit from the use of clear, unambiguous terms for various scales. The U.S. Census provides standardized terms and definitions for several different areawide geography scales. Similarly, the HCM provides terms and definitions for various scales of roadway system elements. To encourage widespread consistency and adoption by practitioners, existing terms and definitions should be drawn from widely used manuals, guidebooks, or references.

Inconsistent Areawide Exposure Measures Despite Similar Travel Survey Data

The units used in areawide exposure measures varied widely, despite many analyses using the same two national travel surveys (i.e., ACS and NHTS) as their base data source. Many analyses used the number of pedestrian and/or bicyclist trips. However, some analyses focused on only journey-to-work trips (directly from ACS data), whereas other analyses included total trips (from NHTS data or combining ACS

and NHTS data). In other analyses, the pedestrian and bicyclist trips were converted to pedestrian and bicyclist miles of travel using estimated trip length data.

If areawide exposure measures use the same base travel survey data, one might expect an emerging consensus on the best approach for using the same or similar trip data to calculate areawide exposure measures. The number of pedestrian and bicyclist trips was a common exposure measure (see Table 1 in Chapter 3), but even with this measure, some analyses reported only on work trips whereas some reported on all trips. Even if consensus on a single areawide exposure measure cannot be achieved, future methodological development in this project should focus on identifying a few good measures that are designated as a best practice for estimating areawide exposure.

Use of Counts in Combination with Models to Estimate Facility-Specific Exposure

One of the most common approaches to estimate facility-specific exposure has been to combine pedestrian and bicyclist counts with estimation models, such that exposure can be estimated for all facilities within a defined geographic area (typically citywide). Even though many cities are now directly collecting pedestrian and bicyclist count data on an annual basis for multiple purposes, these counts are collected at a very limited number of locations. Therefore, estimation models must be used to estimate counts (and exposure) for all the remaining locations where pedestrians and bicyclists cannot be directly counted.

Direct demand models have been the most widely used models for facility-specific exposure estimation so far, and typically use regression analysis to relate directly measured counts to other measured attributes of the adjacent environment (e.g., land use and form, street type, etc.). Assuming that these measured attributes are available citywide, the regression model allows one to extend the sample of facility-specific counts to all facilities citywide. Aside from direct demand models, there are many estimation models in use, including regional travel demand models, GIS-based accessibility models, network analysis models, and simulation-based traffic models.

Given the wide variety of estimation models in place, it will be difficult to single out a single best practice for future methodological development in this project. This project could focus on providing additional guidance on the most common estimation model, the direct demand model, while still acknowledging and providing high-level details on other estimation model approaches.

Similar to areawide exposure measures, the units used in facility-specific exposure measures varied widely. This is also despite the fact that direct measurement and estimation models both produce the same basic data item: counts of pedestrians and/or bicyclists at a point or along a street segment for a defined time interval. As with areawide exposure measures, it may be difficult to achieve consensus on a single facility-specific exposure measure. However, there would be value in defining a few good measures that are designated as a best practice for estimating facility-specific exposure.

Next Steps

Based on the findings and conclusions in this Task 3 report, the TTI-led project team will develop a conceptual framework and design for risk exposure estimation at several different geographic scales (Task 4.A. of this project). The conceptual framework will be based on best practices as identified in this

report, as well as other practices and processes that may be in development (such as those from NCHRP 17-73, Systemic Pedestrian Safety Analyses). The first draft of the conceptual framework will be available for review in May 2017.

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