A MACRO-LEVEL ANALYSIS OF TRAFFIC AND PEDESTRIAN SAFETY IN URBAN AREAS

by

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ABSTRACT

POOYA NAJAF. A macro-level analysis of traffic and pedestrian safety in urban areas. (Under the direction of DR. JEAN-CLAUDE THILL)

The main objective of this research is to examine the effect of city-level urban characteristic, such as urban form and trip generation factors, on traffic safety in general and pedestrian safety in particular. For this purpose, the information for 100 major Urban Areas (UAs) in the United States in 2010 is studied. Factor analysis is applied to construct latent variables from multiple observed variables to measure and describe urban form, macro-level trip generation, citywide transportation network features and traffic safety. Structural Equation Modeling (SEM) is then used to investigate how city-level urban form and trip generation affect traffic safety directly and indirectly (through mediators of transportation network features).

Based on the statistical analysis, it is found that encouraging the use of non-driving transportation modes and controlling traffic congestion, as significant mediators, are effective policies to increase overall traffic safety and pedestrian safety, respectively. In this regard, urban areas with a more even spatial distribution of job-housing balance (more polycentricity), more uniform spatial distribution of different social classes, higher urban density (less sprawl), and more connectivity in their transportation network (more accessibility) have the safest urban form designs.

Moreover, mixed land-use designs with provided local access to services and amenities, food and beverage centers, and religious organizations, followed by strict pedestrian safety standards for neighborhoods are the safest type of land use designs in urban areas. In addition, regulating the off-peak hours allowed time for heavy vehicles and changing the

work schedule of workers who do not reside in the urban area can also help city planners to increase traffic safety.

DEDICATION

To my parents. Without their support and love, none of this would be possible.

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LIST OF ABBREVIATIONS

WHO	World Health Organization
USDOT	U.S. Department of Transportation
GDP	Gross Domestic Product
UAs	Urban Areas
VMT	Vehicles Miles-Traveled
GNP	Gross National Product
TAZs	Traffic Analysis Zones
FA	Factor Analysis
SEM	Structural Equation Modeling
CBD	Central Business District
ITS	Intelligent Transportation Systems
WRI	World Resources Institute
SOVs	Single Occupancy Vehicles
HOVs	High Occupancy Vehicles
UMR	Urban Mobility Report
ACS	American Community Survey
LTPP	Long-term Pavement Performance

TTI	Travel Time Index
EFA	Exploratory Factor Analysis
CFA	Confirmatory Factor Analysis
PA	Path Analysis
PCA	Principal Component Analysis

CHAPTER 1: INTRODUCTION

1.1. Background

More than 1.17 million people die and over 10 million are injured annually in traffic crashes around the world. Traffic crashes were estimated to be the world's ninth most important health problem in 1990, in a study by the World Health Organization (WHO), Harvard University and the World Bank [1]. The study predicted that traffic crashes would move up to be the third largest cause of death and disability in the world by the year 2020 [1]. More than 32,700 traffic crash deaths were reported among U.S. residents in 2013 [2]. The annual economic cost of traffic crashes was estimated to be 242 billion dollars by U.S. Department of Transportation (USDOT) [2]. Lost productivity, medical costs, legal and court costs, emergency service costs, insurance administration costs, congestion costs, property damage, and workplace losses are the main costs of traffic crashes. These costs are estimated to be 1.6 percent of the real U.S. Gross Domestic Product (GDP) in 2010 [3].

Global urbanization and motorization trends have made traffic safety one of the primary challenges for city managers and planners, especially those serving in Urban Areas (UAs), since they are more prone to suffer from traffic crashes compared to rural areas [3, 4]. A study by Cambridge Systematics [5] shows that the costs of traffic crashes always exceed the cost of congestion in UAs. The costs of traffic crashes in very large UAs, with a population of more than three million, are almost double those of congestion. In small UAs, with a population of less than 500,000, where congestion is not a critical issue, the costs of traffic crashes rise to more than six times congestion costs. Traffic crashes are also regarded as the costliest societal side effects among all transportation-related issues, such as environmental and social problems. The average death rate by traffic crashes for the 50 most populous U.S. metropolitan areas was 8.2 per 100,000 residents in 2009, with a range from 4.4 to 17.8 [6]. The average national death rate by traffic crashes was 1.11 per 100 million vehicles miles-traveled (VMT), ranging from 0.56 in the District of Columbia to 1.96 in Montana [2]. The considerable variability within this range demonstrates the need for more research to understand how urban characteristics affect traffic safety, and particularly what factors make a UA safer than another so as to better inform city managers and policy makers.

More than 80 percent of the U.S. population lives in UAs, based on 2010 Census information [7]. Rising urbanization and motorization trends in cities constitute one of the primary challenges contributing to traffic crashes with the number of privately owned cars globally reached one billion in 2010 [8]. In order to improve traffic safety in UAs, it is essential to monitor and then analyze all system elements related to transportation such as traffic flow, users (including drivers, passengers and pedestrians), vehicles (including bikes, passenger cars and transit utilities), infrastructure (including roadways and traffic control devices), transportation network and behavioral patterns, as well as urban areas land-use patterns [1]. A comprehensive traffic safety plan for a city, as a complex system, must cover the aforementioned components at the aggregate city-level. Therefore, a variety of components that make a city a complex system, may impact traffic safety. City characteristics (e.g., population density, density of trip attraction and production centers, weather, spatial structure, service-food condition and others), household characteristics (e.g., age, race, income, household size, education, car ownership and others), traffic flow (e.g., congestion, traffic density, presence of heavy commercial vehicles and use of single-occupant vehicles), roadway condition (e.g., pavement condition), transportation network features (e.g., travel time, network density, connectivity and layout) and share of active transportation modes (i.e., modal share of transit, passenger car, bike and others) are the main components of a UA from a transportation planning perspective. Indeed, improving traffic safety in a UA requires the participation of multiple involved parties.

One of the most important characteristics of a UA is urban form (also known as urban spatial structure). Urban form is generally defined as "the physical shape and structure of the city" which impacts large-scale plans and policies for the UA including transportation related policies as well as residents' daily lives [9]. Transportation planning in UA is strongly correlated to urban form (i.e., urban form can shape transportation related activities and vice versa), as they are the main features of urbanized areas that determine how residents interact with each other spatially [10]. On the other hand, many of the elements of UAs, which influence traffic safety, are directly or indirectly representative of urban form. Consequently, it is crucial to study the relationship between urban form and traffic safety. Urban form consists of three separate designing and planning levels, including street-level, community-level and city-level. Trying to meet the traffic safety requirements has been conventionally one of the main basic assumptions of urban form planning at the street- and community-level [11], however there is a lack of research to determine the role of urban form design at the macro level (i.e., city-level urban form) on traffic safety practices.

Other characteristics of a UA, including traffic flow condition, roadway characteristics, household characteristics, share of different transportation modes and other transportation network features can generally be categorized by two macro-level groups: urban transportation network characteristics and urban trip generation characteristics. Every aspect of transportation is in some way related to the trip generation or transportation network. These two groups of characteristics along with urban form will form the three main groups of urban features. While traffic safety, in a broad sense, is expected to be influenced by these groups of attributes, there is a gap in the traffic safety literature regarding the simultaneous and integrated effect of aggregate-level urban trip generation characteristics, macro-level urban transportation network characteristics and urban form features on traffic crashes.

Accounting for 80 percent of the world's GDP, cities are known as "engines of growth" [12]. To keep this engine working well, policy makers need to provide efficient and safe transportation means for the flow of people and goods. Efficiency and safety are both vital paradigms for a comprehensive sustainable urban development plan [13]. Well-planned UAs must offer multiple sustainable (i.e., efficient and safe) mobility options to improve the quality of life and maintain accessibility to various opportunities [12]. Long- and mid-term traffic safety plans are necessary to meet sustainability objectives in UAs by providing different opportunities for public users, improving the economy and saving lives since traffic crashes costs equate to 1 to 3 percent of a country's annual Gross National Product (GNP) [1]. Studies show that sustainable urban forms (e.g. integration of sustainable transportation modes, higher density, better street connectivity, and compact and mixed-use land development) improve traffic safety [14]. The United Nations has called 2011 to 2020 the "Decade of Action for Road Safety". The objectives of this initiative is to reduce rate of fatalities by 50 percent in this decade. Considering the traffic safety in sustainable urban planning is a first step to achieve this goal [14].

A "pedestrian-friendly environment" is a primary concept in urban planning which talks about how to provide better access to transit and walkable areas for pedestrians in UAs [15]. When it comes to planning for pedestrian-oriented designs and walking activities, pedestrian safety receives considerable attention and importance. About 14 percent of traffic fatalities in the US (4,735 out of 32,700) have been pedestrian fatalities in 2013. "On average, a pedestrian is killed every 2 hours and injured every 8 minutes in traffic crashes in the US", which demonstrates the importance of pedestrian safety planning along with the general traffic safety planning in urban planning [16]. On the other hand, many general policies used to control transportation network-related activities influence pedestrian activities and consequently pedestrian safety as well. Urban planning, traffic safety planning and pedestrian safety planning are practically and theoretically interrelated and integrated concepts. With increasing motorization in UAs, traffic congestion (and traffic volume in general) increases and consequently conflicts between pedestrians and motor vehicles increase as well. The expected risk of pedestrian-related crashes is directly dependent on the number of conflicts between pedestrians and vehicles. Hence, a better understanding of associated urban characteristics with pedestrian safety at the macro level is necessary to achieve a sustainable and safe urban environment.

1.2. Research Objectives

This research contributes to the traffic safety literature through a macro-level analysis of traffic crashes in US urban areas considering urban characteristics, such as urban structure and trip generation attributes. The objectives of this research can be divided into two different levels (primary and secondary objectives) to answer the research questions explained in section 1.3. Since this research studies the relationship between macro-level urban characteristics and traffic safety, primary objectives are the ones that are directly related to traffic safety policy-making (whether general traffic safety planning or specific pedestrian safety planning) in UAs; while the secondary objectives of this study are indirectly related to traffic safety or other characteristics of UAs.

1.2.1. Primary Objectives

1- To identify the relationship between macro-level urban form and traffic safety: the rate of fatal crashes per unit population in a UA is considered as the safety performance measure in this research [17]. One of the main objectives is to identify the effects of city-level urban form (urban structure) on crash incidence in UAs. Statistical modeling helps to evaluate the significance and effect of different macro-level urban form characteristics on crash rate.

2- To identify the relationship between macro-level urban trip generation and traffic safety: the second primary objective of this research is to study the role of aggregate trip generation characteristics on crash rate. Statistical analysis explains the significance and effect of urban trip generation characteristics on the incidence of fatal crashes in UAs.

3- Developing an integrated framework for urban planning considering traffic safety: urban form, trip generation characteristics and transportation network characteristics are the most important elements of a UA required to study traffic safety. One of the main objectives here is to develop an integrated model suitable to summarize three aforementioned models (in additional to other ancillary transportation network characteristics) into a single modeling framework that clarifies the role and significance of different urban features on crash rate. This integrated modeling framework can assist policy makers to more comprehensively consider traffic safety in urban planning, given the multidimensional complexion of city environments.

4- To identify the relationship between macro-level urban characteristics and pedestrian safety: the final primary objective of this study is to study the role and significance of different urban features (such as urban form and transportation related characteristics) on pedestrian safety. Statistical analysis can illuminate the effect of a variety of urban characteristics on the incidence of pedestrian fatal crashes in UAs. Statistical differences between pedestrian safety and overall traffic safety models can underscore the urban factors that increase pedestrian safety, as one of the main paradigms of walkability, in UAs.

1.2.2. Secondary Objectives

1- Categorizing the urban characteristics into urban form and trip generation characteristics: as discussed earlier, there is a fuzzy area in the definition of urban features when categorizing urban characteristics into two main groups of characteristics, including urban form and trip generation. For instance, employment density is an element of urban form as it defines the intensity of activities in a UA. However, this variable is a measure of trip generation as well, as it attracts commuters and increases trip generation. Thus, one of the secondary objectives of this research is to more explicitly distinguish between urban form, trip generation and also transportation network characteristics.

2- Defining factors for urban form and trip generation: as discussed earlier, there are several variables in each category of urban characteristics. One of the secondary objectives of this research is to combine similar attributes into common factors and introduce new factors to measure urban characteristics. As urban form encompasses multiple possible indicators or measures, the objective is to identify operational metrics that can be combined into common factors to measure urban characteristics that influence traffic safety. For instance, job density and population density are both representative of density in UAs. These two variables could be reduced to one single common factor.

3- To clarify the limitations: this research deals with many complex relationships between several variables. One of the secondary objectives of this study is to clarify the limitations in terms of data availability, statistical analysis, implementation issues and policy making for future studies.

1.3. Research Questions

1.3.1. Urban Form and Traffic Safety

Many research has been performed to evaluate different aspects of urban form. Most of this research has evaluated designing and planning policies at street- and community-level urban structure. Transportation safety (e.g., pedestrian and vehicle safety) has always been considered as the main factor to consider in the built environment and when design streets and communities [11]. Roadway functional classification, the level of pedestrian activities, retail configuration, neighbor and community density, development patterns (e.g., transit oriented development, sprawl and suburban development), block size, type and level of accessibility, development of commercial and residential land uses, mixed use environments, convenient walking distances, walkable developments, level of connectivity, local street configurations, sight distances, type of intersections, number of conflict points, design treatments, street widths, street lighting and the existence of roadside parking are some of the effective street/community-level urban form factors examined in the traffic safety literature [18, 19].

As discussed earlier, most of the aforementioned attributes have been studied at the micro-level (street- and community-level) in the urban planning literature. However, there is a gap in research on the relationship between macro-level (aggregate-level) urban features and traffic safety, which underscores the need for this research. To study the relationship between macro-level urban form planning and traffic safety policy making, the following research questions are addressed:

1) How to best define macro-level urban form to study traffic safety? What are the strong factors of urban form, at the aggregate level, that influence traffic safety?
2) What is the relationship (both strength and direction) between the factors of urban form and traffic safety?
3) What specific city-scale land-use strategies in planning practices have the potential to improve traffic safety?

1.3.2. Urban Trip Generation and Traffic Safety

Traffic volume is the first and most important component of transportation when it comes to studying traffic safety. To estimate the traffic volume on the roadways, four-step transportation models are conventionally used. Trip generation is basically the first step in the conventional four-step transportation models used to predict travel demands in Traffic Analysis Zones (TAZs). Since trip generation is the starting factor to estimate traffic volume, and since traffic volume is the most important point in estimating traffic safety, it is important to study the direct and indirect effects of trip generation on traffic safety. Trip generation characteristics are differentiated as trip production and trip attraction parameters [20]. Discrete choice models, regression models and cross classification techniques are used to estimate trip generation at the disaggregate level for individuals, TAZs and homogenous groups of users, respectively [21]. Since trip generation is the first step to study the behavior of people and goods that travel to and from particular locations, the type of activity (e.g., land-use type) at those locations is an effective factor in the trip generation process [22]. However, at the macro level (city-level), trip generation characteristics consist of every aspect of transportation in a UA that generates (produces or attracts) trips, including urban characteristics and household characteristics [23].

Urban characteristics such as population density, land-use type, land development, transportation infrastructure [24], geographic characteristics, trip attractors' characteristics [25], employment density, parking condition, growth factors, transit services, sidewalk availability, peak hours [26], available transportation modes, spatial factors (e.g., occupation of urban streets and changes in the geometry of streets), economic factors (e.g., real estate valuation, travel time and travel cost), environmental factors (e.g., noise, air and visual pollution and temperature change), social factors (e.g., access to services and public equipment), density of shopping and retail centers [27], city size, existence of trip attraction hubs [28] all can be considered as effective factors to estimate trip generation in a UA. In addition, household and socioeconomic characteristics such as gender, age, income level, educational level [28], household size, car ownership, employment condition and commuting time [29] can be also considered as intervening factors to estimate trip generation in UAs. The following research questions will be at the center of our study of the effect of the trip generation characteristics on traffic safety:

1) How to best distinguish between urban form and urban trip generation characteristics, since there are several common elements between these two groups of urban features?

2) How to define macro-level urban trip generation characteristics in order to study traffic safety? What elements of UAs can be indicators of urban trip generation?
3) What is the relationship (both strength and direction) between the factors of urban trip generation and traffic safety?
4) How should traffic safety be considered in future trip generation planning? How to control urban trip generation to target traffic safety?

1.3.3. Integrated Macro-Level Framework for Urban Traffic Safety

There is a substantial body of research examining the relationship between transportation network characteristics and traffic safety. Most of this research models traffic crashes (frequency or severity) at the disaggregate level using different transportation network characteristics, including modal split (share of different modes such as bike, passenger car and transit), characteristics of roadways (e.g., roadway alignment, number of lanes, lane width, road surface type, road surface condition and geometric design), traffic flow characteristics (e.g., traffic density, traffic congestion, volume over capacity, peak-hour volume, vehicle-miles travelled, presence of heavy vehicles, traffic control devices and speed limit), environmental characteristics (e.g., lighting and atmospheric condition), vehicle characteristics (e.g., unit type, vehicle configuration, vehicle model, weight, length, height, width and speed), and occupant characteristics (e.g., age, gender, seating position, ejection condition and alcohol test result). These attributes have been mostly defined at the disaggregate level to study traffic safety on road segments, TAZs or even individual crashes [24, 30 and 31]. There is a gap in the safety literature to define macro-level (aggregate level) transportation network characteristics for UAs and study the effect of these urban features on traffic safety. This research tries to fill this gap as well.

Urban form and trip generation are the main groups of urban features to consider when examining traffic safety in this research. After studying the effect of each group of attributes individually, an integrated framework is necessary to clarify the level of relative importance of each group of characteristics. This integrated framework will help policy makers understand the role of the most significant elements of urban characteristics in traffic safety planning. To develop this integrated modeling framework, the following questions will be addressed:

1) How to best combine the main groups of urban features (i.e., urban form characteristics and urban trip generation characteristics) to present an integrated model that represents the most significant features of UAs?
2) What is the relationship (both strength and direction) between these significant features of UAs and traffic safety?
3) What are the most important criteria for transportation policy makers to consider in order to increase traffic safety in UAs?

1.3.4. Pedestrian Safety

As discussed earlier, pedestrian fatalities represent about 14 percent of total traffic fatalities in the US; however, pedestrians account for only 10.9 percent of trips [32]. This issue is even more critical in populated urbanized areas where walkability, pedestrian activities and accessibility to different mixed land-uses are the basic elements of urban planning. There is abundant research on pedestrian safety at the micro-level (street- and community-level), however there is a lack of research on the effect of macro-level (city-level) characteristics of UAs on the incidence of pedestrian crashes. There are some questions to address to fill this gap in the literature:

1) What is the relationship (both strength and direction) between significant features of UAs and pedestrian safety?
2) What factors are going to differentiate pedestrian safety from the overall traffic safety? How statistically different is the pedestrian safety model than the models of overall traffic safety?
3) What are the most important criteria for transportation policy makers to consider in order to increase pedestrian safety in UAs?

1.4. Structure of Dissertation

The rest of this dissertation is organized as follows:

Chapter 2 reviews the existing literature on the relationship between urban form and trip generation characteristics with traffic safety. Chapter 3 (data description) explains the data and introduces the data collection process, sources of data, studied variables and their characteristics. Methodology and technical aspects of this research, including Factor Analysis (FA) and Structural Equation Modeling (SEM) are introduced in chapter 4. The relationships between urban form and traffic safety (both overall traffic safety and pedestrian safety) are modeled using FA and SEM techniques and the modeling results are explained in chapter 5. The relationships between trip generation characteristics and traffic safety (both overall traffic safety and pedestrian safety) are modeled using FA and SEM techniques and the modeling results are explained in chapter 6. Chapter 7 examines the relationship between all significant urban features (i.e., urban form, trip generation characteristics and transportation network characteristics) and traffic safety (both overall traffic safety and pedestrian safety) and introduces an integrated framework to model this relationship. Significant factors of urban characteristics and their effect on traffic safety are introduced in this chapter. Chapter 8 summarizes the outcomes of the dissertation research and draws some practical conclusions and policy implications from the results.

CHAPTER 2: LITERATURE REVIEW

2.1. Introduction

Conceiving a UA as a complex socio-physical system encompassing city characteristics, household characteristics, traffic flow, transportation network characteristics and roadway condition, a range of UA components that are anticipated to affect traffic safety are reviewed in this chapter. Urban form at different levels and its measures are first defined. The relationship between urban form and traffic safety is then reviewed. The relationship between urban trip generation characteristics and other macro-level urban characteristics with traffic safety is reviewed in this chapter as well. In addition, pedestrian safety in UAs and its relationship with urban features is reviewed. Finally, conclusions, lessons learned from the literature review and limitations are summarized in this chapter.

2.2. Traffic Safety and Urban Form

2.2.1. Urban Form

In a broad sense, urban form may be defined as the arrangement of different elements in a UA, including urban public spaces. The spatial structure of the UA influences many different urban features such as traffic safety, accessibility, sustainability, efficiency, equity, environment and economics. Several measures have been used to represent urban form [33, 34]:

- City shape: this parameter measures whether the shape of the city is circular. How much the UA deviates from a circular shape is defined as the city shape. The major and minor axes of a hypothetical ellipse that has the same area as the UA can be measured and their ratio (ranging from 0 to 1, where 1 indicating a circular UA) is the measure of city shape.

- Density of transportation network: this parameter measures the density of the roadways in the UA.
- Spatial distribution of population: this parameter measures how the population is distributed with respect to the Central Business District (CBD).
- Job-housing balance: this parameter measures the ratio of jobs versus housing in a unit of area, such as a census tract.
- Pattern of residential land-uses: this parameter measures the distribution pattern of residential areas in the UA. The gradient of the population density is the best measure to study the pattern of residential land-uses in a circular UA. This measure basically represents the centralization of the population around the CBD area.
- Population centrality: “To create a measure of population centrality that is less correlated with city area, one can plot the percent of population living within x percent of the distance from the CBD to the edge of the urbanized area against x and compute the area between this curve and a 45- degree line representing a uniformly distributed population.” [33]
- Employment centrality: this parameter is another measure of urban form which is calculated in a similar manner to the population centrality measure.
- Employment density gradient: this parameter is also the other indicator of urban form and measures spatial variation in density over an area.

Urban form features can be defined at three different levels:

- Street-level urban form: streets of a UA should be designed in such a way to accommodate different types of users (e.g., pedestrians, passenger cars, transit vehicles and trucks), different types of facilities (e.g., traffic control devices, transportation equipment and transit stations) and different types of functions (e.g., vehicle movement, bicycle movements, pedestrian activities, shopping and recreational activities). The design of streets has to address several different standards, including roadway design standards (e.g., speed limits, minimum sidewalk widths, lane width, maximum corner radii, parking condition on the roadside, etc.), public improvement standards (e.g., spacing, lighting type, height, illumination level, the improvements in vicinity of transit stops, planting, etc.), site development standards (e.g., pedestrian access and entrances, design of parking, utilities and signage), bicycle route standards, and safety and security codes [35].
- Community-level urban form: communities have primary responsibility to serve the basic needs of residents and other daily users and provide facilities and opportunities to residents for different types of neighborhood activities. Community design is essential to the livability while designing and locating several activity centers, such as schools, parks, libraries, cultural facilities, police stations, mixed-use buildings and nighttime activities facilities, are the main functions of community-level urban form [35].
- City-level urban form: the overall existing physical and activity-based form of a city, planning for the future growth (e.g., planning for transit-oriented developments, community centers, neighborhood districts and corridors), planning

for existing and future land-uses (e.g., commercial, residential and mixed-use areas) and also planning for future development of the UA (i.e., how to design corridors, transit systems, community centers, pedestrian-oriented commercial centers, mixed-use areas and industrial areas to maximize the efficiency of the urban activities) are some of the main functions of the city-level urban form [35].

2.2.2. Urban Form at the Street- and Community-Level

Residents of a UA deserve to live in a well-designed, safe and secure area. Proper design and effective use of the built environment which increases user safety at all times of the day is a major objective of urban planning [35]. Traffic safety has been the main concern for design practices and development of conventional streets and communities. There exists much prior research that focuses on the relationship between street- and community-level urban form and traffic safety [11].

Pedestrians and bicyclists are two major users of a transportation network. These two modes of transportation (walking and bicycling) are the cleanest modes and are essential elements of sustainability as well. However, traffic safety issues are unfortunately more precarious and dangerous for the users of these two modes, because safety of motorized vehicles has been mostly considered as the only priority to ensure safety in the urban design. In fact, a higher risk of injuries and fatalities in UAs exist for pedestrians and bicyclists and is an important concern of traffic safety policy makers. Ensuring the safety of non-motorized users in street-level urban form design, speed control by either Intelligent Transportation Systems (ITS) devices or street design, creating denser layout of streets with narrower cross sections, and reducing the size of residential neighborhoods are suggested as the efficient policies to address this issue [36]. “Adequate lighting, clear definition of outdoor spaces, fencing, use of landscaping as a natural barrier, secure storage areas, good visual connections between residential and public environments" are some other street-level policies used to increase traffic safety [35].

Studies [8] have shown that implementing urban design and land-use policies and practices at the community-level should be priority considerations for practitioners and decision makers to increase the safety and public health when studying the urban form at the community-level, it is found that urban arterials, arterial-oriented commercial developments and big box stores are generally associated with a decrease in traffic safety. Alternatively, higher-density communities and traditional pedestrian-scaled retail configurations are associated with an increase in traffic safety [11]. Traffic safety may be increased by the safe designing of access points to the arterial thoroughfares, locating commercial land-uses and retail centers far away from higher level roadways, and controlling the speed on the access lanes to arterial thoroughfares [11, 37]. "Slow residential streets" can represent another policy to increase the traffic safety in a community through the use of speed bumps, and diagonal parking or widening sidewalks and narrowing streets. Generally, mixed-use development represents one of the most important policies for community-level urban planning to increase traffic safety as well as efficiency [35].

2.2.3. Urban Form at the City-Level

To date, the existing literature on urban planning has mainly focused on street- and community-level (local- and neighborhood-level) characteristics of the urban form and the built environment. There has not been much research carried out on the effects of macro-level (urban-level) characteristics of the built environment on transportation issues.

Research has shown that macro-level urban form can be as influential as micro-level features on people's travel behavior [38]. Consequently, traffic safety is expected to be influenced by these characteristics as well. As discussed earlier, the main focus of this research is to study the relationship between macro-level urban characteristics and traffic safety in order to fill this gap in the existing literature.

Mohan [36] studied traffic fatality data in American cities with a population greater than 100,000, in addition to 56 large cities around the world. Results showed that simply improving vehicle safety and roadway conditions would not be enough to significantly decrease the fatality rate, because of the wide variation in fatality rates across and within different income levels. Urban form was then suggested as one of the main factors that determine the fatality rate in a UA.

Cities Safer by Design is a new report by the World Resources Institute (WRI) Center for Sustainable Cities [39] that suggests the best practical solutions to improve traffic safety in UAs. These recommendations are covered in 5 basic urban design elements [39]:

- Block size: blocks should be 75-150 meters to improve traffic safety and walkability. Large blocks allow vehicles to increase travel speed, due to less traffic flow interruptions, which is not safe for pedestrians.
- Connectivity: improving the connectivity between multiple transportation modes and creating multiple routes for bikes and pedestrians helps to decrease travel distances.
- Lane width: reducing street width increases the street availability for pedestrians, bikes and parking. Average traffic speed is lower in narrow lanes as a result of

increased driver awareness.

- Access to destinations: it is recommended to plan transit, parks, schools, and stores within a walking distance (<0.5 kilometer) from communities. Accessibility to different public services decreases the need to travel and improves traffic safety.
- Population density: increasing density by 100 persons per square mile, decreases traffic crashes by 5 percent, without any change in VMT, street design and land use.

As mentioned in the discussion about micro-level urban form, public health is an important factor to consider in urban planning at both the micro- and macro-level. Different modes of transportation have different impacts on public health; motorized transportation modes generate negative consequences in the UA, including air quality issues and potential risks for walking and biking [40].

Based on the spatial pattern of employment layout, a city's urban form can be generally divided into monocentric and polycentric city models. The monocentric configuration [41] has been the first formal model of urban structure with a unique center, CBD. In contrast, in polycentric UAs, the proportion of employment in the CBD is lower and some other employment centers are located outside the CBD; the employment distribution has become more even as a result [42].

Urban sprawl is another major urban form factor associated with traffic safety. Urban sprawl is the low-density spreading of urban development onto undeveloped lands near the UA fringe. This development pattern increases the need for vehicles and consequently decreases traffic safety. Urban sprawl increases the risk of traffic crashes not only by increasing VMT, but also by decreasing the density and compactness of development in the UA. Increasing density is often associated with mixed land-use development in smaller areas, enhancing walkability and reducing traffic fatalities [43]. However, there are several definitions possible for urban sprawl. Principal Components Analysis (PCA) has been used in recent research [43] to create a sprawl index, using data for 448 US counties in the largest 101 metropolitan areas. Thus, urban sprawl is defined in this study as an environment with “a population widely dispersed in low-density residential development; rigid separation of homes, shops, and workplaces; a lack of distinct, thriving activity centers, such as strong downtowns or suburban town centers; and a network of roads marked by very large block size and poor access from one place to another” [43].

Ewing et al. [43] devised a compactness index and tested it as an influential factor for the incidence of traffic fatalities. Their study showed that traffic fatality rates are higher in areas with higher levels of urban sprawl. The results showed that for every 1% increase in the index (i.e., less sprawl), the fatality rate, especially the pedestrian fatality rate, decreases by 1.49%. Ewing et al. [44] have recently upgraded these results using an SEM technique. Their findings confirm that urban sprawl is both directly and indirectly a significant risk factor for traffic fatalities.

Frumkin [45] discussed the impact of features of sprawl (i.e., low density and segregated land use and high dependence on passenger cars for transportation) on traffic crashes, pedestrian injuries and fatalities. He argued about the positive role of social equity and justice in urban design and the need for better planning to reduce public health costs such as traffic crashes. Increased law enforcement can be another effective policy for cities to reduce fatal crashes according to Redelmeier et al. [46].

2.3. Traffic Safety and Urban Trip Generation Characteristics

Related research reveals that, in addition to transportation and roadway characteristics, trip production and trip attraction are vital elements in traffic safety analysis and when modeling the crash rate at the aggregate level [47]. Trip production and trip attraction are also primary steps used in the transportation network modeling process, the traditional four-step model, which results in the estimation of traffic volume on roadways. Estimated traffic volume can then be used to estimate aggregate crash rate [48]. The relationship between trip production and trip attraction characteristics with traffic safety is reviewed in this next section.

2.3.1. Urban Trip Production Characteristics

Trip production characteristics are associated with the source of travelers' trip generation. Several aggregate-level characteristics in UAs are associated with the generation of trips; some of them are related to general urban characteristics, such as population, density, number of commuters and employment; some others are household (user) characteristics, such as income-level, car ownership and ethnicity. The relationship between some of the major trip generation characteristics and traffic safety is reviewed here.

Population size, population density and number of commuters in a UA are some of the effective factors used to estimate the number of crashes at the macro level. The high risk of injuries and fatalities in more populated UAs, especially for pedestrians and bicyclists, is a critical safety issue [36]. Studies have shown that population density is a major factor associated with crash rate in UAs, where UAs with higher population densities generally have lower crash rates. Residents of UAs with higher densities tend to drive less;

thus their overall exposure to crashes is lower compared to an average UA. While the safety benefits of higher densities are minor when they are examined at the community-level, the aggregate reduction in crash rate across the larger population of a UA is notable [11]. In addition to population density (i.e., persons per unit area), density can also be measured in other ways, such as the employment rate, commuters and housing per unit area, and also development density [38].

Household income is introduced as an important household feature that affects traffic safety. The likelihood that people accept and follow traffic safety rules and policies increases with their income level [49]. The distribution of traffic injuries is also influenced by income level. Poor households within poor areas count for a disproportionate negative factor of traffic crashes. Fatality rates (i.e., deaths per 100,000 population) in low- and middle-income areas are six times the rate for high-income regions. The fatality rate's variation even within these low- and middle-income areas is huge. Poor households mainly contain pedestrians, cyclists, transit users and truck drivers who are therefore expected to suffer more from traffic crashes [50, 51].

Employment is another effective macro-level urban characteristic that has been the focus of the traffic safety literature. Research by Partyka [52] demonstrates that an increase of 1,000 in the number of unemployed workers decreases the number of fatalities by 1.86 while an increase of 1,000 in the number of employed workers increases the number of fatalities by 0.50. Overall, mobility is introduced as the main reason for traffic crashes. "A major side effect of increased mobility is increasing exposure to injury in traffic crashes" [52]. Since car ownership is an important element to measure the degree of mobility in a UA, it is also a significant factor to study traffic safety.

With population growth, transportation facilities and network capacity need to be enhanced. Constructing more highways, increasing public transportation and enhancing green transportation infrastructures (e.g., bicycle routes and pedestrian pathways) are some of the ways to meet the new traffic demand [53].

Traffic-related issues gain even more importance when governments have to prioritize different strategies for funding allocations. Generally, “Republicans tend to favor adding capacity to the street/highway network to allow people to follow their revealed preference for the automobile, while Democrats tend to favor other modes in a bid to improve the sustainability of the UA.” In fact, the political process, and thus political parties plays an important role in the long-term transportation planning and accordingly traffic safety planning [54].

GDP is another important factor of urban traffic safety. Kopits and Cropper [55] showed that traffic fatality risk (i.e., the number of fatalities per 10,000 persons) first tends to increase and then decrease with GDP per capita. Figure 2.1 presents fatality risk versus GDP per capita for all studied years and countries covered in this research, and depicts an inverted U-shaped pattern. HD1 represents highly developed countries (i.e., countries that have a human development index of 0.8 or greater) while HD2 represents other countries in Figure 2.1. As GDP per capita increases at the initial stages of development, traffic safety tends to worsen. However, at higher levels of GDP per capita, growth in motorization decreases and governments invest more in traffic safety. At this stage of development, traffic safety increases and the fatality risk decreases.

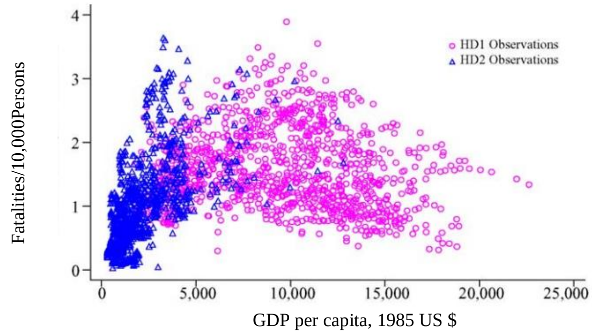

FIGURE 2.1: Traffic fatality risk versus GDP per capita [55].

Travel behavior in a UA is mainly influenced by users' characteristics. Households form different groups of users, including drivers, passengers, pedestrians and users of public transit. Thus, household characteristics taken at the aggregate level of a UA encompass user characteristics that are effective factors of traffic safety. For instance, pedestrian children in low socio-economic groups are more likely to be killed in traffic crashes compared to children in high socio-economic groups [56]. The risk of users' involvement in traffic crashes is strongly related to their socio-economic and demographic characteristics (e.g., ethnicity, gender, age and education) according to Factor et al. [57] who also indicated that the risk of traffic crash involvement is lower for males and users with higher education and socioeconomic status in comparison to others. Other research [58] shows how vulnerable groups are highly influenced by traffic safety policies.

Treno et al. [59] modeled alcohol-related traffic crashes in 581 defined zip code areas in California using many different attributes, including demographic characteristics. They showed that household size is a significant variable to model traffic crashes. The risk of traffic crashes in zip code areas with higher average household size is generally higher, based on their results, where household size is associated with a 3.18 percent increase in residence-based injury accident rate. Age and gender are other household characteristics associated with traffic safety. It has been expressed that males perceive some driving behaviors as generally less likely to cause a traffic crash compared to females [60]. Zhang et al. [61] showed a significant difference in traffic safety by age groups. For instance, young drivers get involved in more risk-taking conditions, such as alcohol and drug use, speeding and overtaking maneuvers. On the other hand, elderly drivers deal with more medical and physical conditions, inattention and improper turning. Although many studies have examined the effect of the driver's age and gender on traffic crashes' severity, type and frequency at the disaggregate level, the gender ratio and the average age of residents (who include all kinds of users of the transportation network, such as drivers, pedestrians, passengers, bicyclists and users of public transit) at the aggregate level are our focused variables in our research.

Ethnic differences represent another household characteristic that influences traffic crashes, as studied by Schiff and Becker [62]. Their results from a 33-year study period found that Native Americans had fatality rates 2-3 times higher compared to Whites; Hispanic males also had higher fatality rates than White Non-Hispanic males. In another study, it was concluded that a subgroup of Hispanics who have no valid driver license may be involved in significantly more traffic crashes than those with license [63]. The level of education in general, accessibility to information, public knowledge, safety education and drivers' training are other important user characteristics that influence traffic safety. To increase traffic safety among young drivers, many states require some level of driver's education for drivers under a certain age to be qualified for a driving license [64]. Another significant household characteristics is marital status. Studies show that "single drivers have a higher violation rate in all types of traffic violations" [65]. Lagarde et al. [66] studied the effect of separation and divorce on traffic safety and concluded that marital separation or divorce is associated with an increase in severs traffic crashes.

In summary, many household and urban characteristics that are regarded as trip generation features play a significant role in transportation planning and specifically in traffic safety modeling.

2.3.2. Urban Trip Attraction Characteristics

Trip attraction characteristics are mainly considered as the reason and motivation of travelers' trips to meet their need at their trip destination. There are several aggregate-level characteristics that are known to attract trips; some of them represent general urban characteristics, such as employment density. The relationship between some of the major trip attraction characteristics and traffic safety is reviewed here.

Employment density (employment per capita or employment per unit area) is one of the most significant variables in transportation planning, since it has strong direct correlation with trip attraction and traffic volume. Kim et al. [67] modeled the crash frequency of grid-based cells (uniform cells of approximately 0.1 mi^2) in the city and county of Honolulu, Hawaii, using population and employment data. Figures 2.2 and 2.3 show the linear relationships between the population number versus the number of traffic crashes and the employment density (the number of employment per 0.1 mi^2) versus the number of traffic crashes, respectively, grouped by crash type: bike-related, vehicle-to-vehicle, pedestrian-related and total crashes.

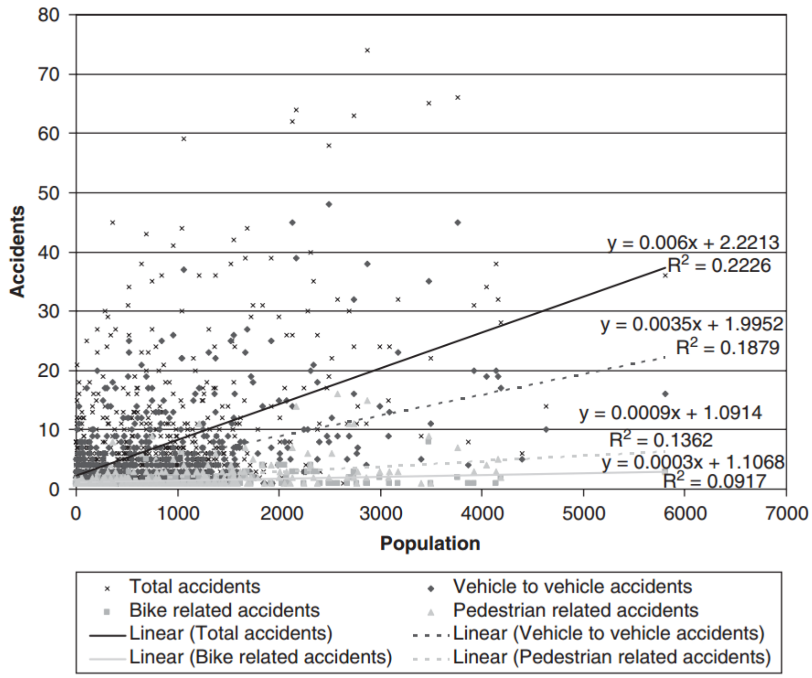

FIGURE 2.2: Linear relationship between population and number of traffic crashes [67].

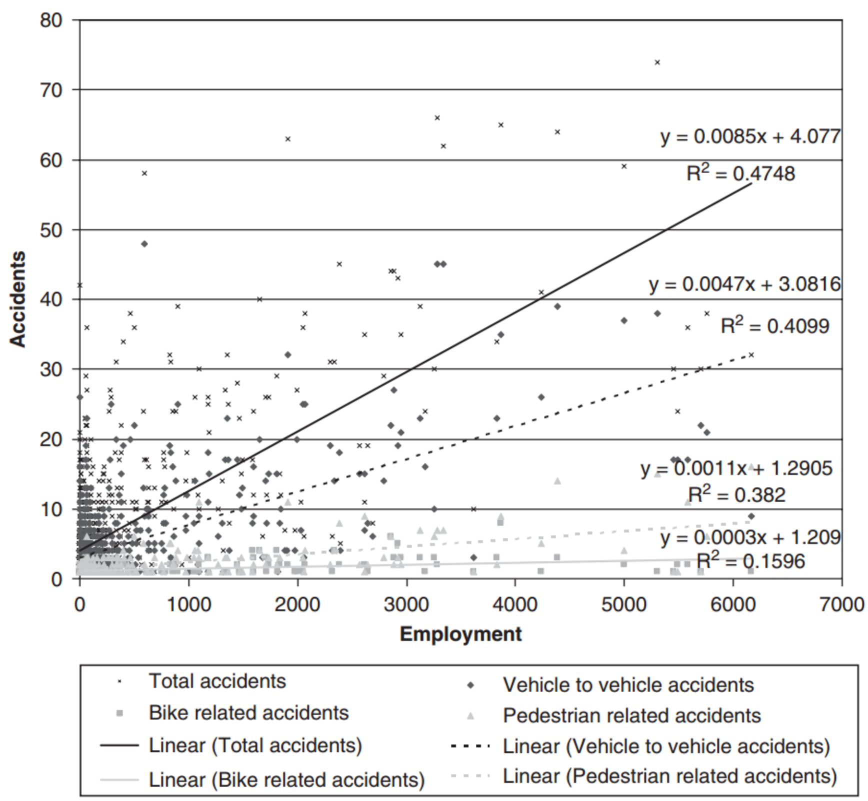

FIGURE 2.3: Linear relationship between employment and number of traffic crashes [67].

Figure 2.3 focuses on where people live instead of where they work. It is worth mentioning that goodness of fit (R-squared) values for employment-based models are much higher compared to population-based models for all type of crashes, including bike-related crashes, vehicle-to-vehicle crashes and pedestrian-related crashes as well as total crashes (47% vs 22%, 40% vs 18%, 38% vs 18%, and 15% vs 9%) [67]. These results demonstrate the significant effect of trip attraction characteristics (e.g., employment density) compared to trip production features (e.g., population density) on traffic safety. Employment density is also associated with pedestrian activities and consequently is one of the main predictors of pedestrian crashes [68].

There are several notable trip attractors in a UA, such as grocery stores, restaurants, cafes, bars, fitness centers and religious organizations. Abdel-Aty et al. [47] studied the effect of many trip attraction characteristics, such as home-based trip attractions, school trip attractions, social recreational trip attractions, airport trip attractions and shopping trip attractions on traffic crash modeling and concluded that trip attraction characteristics provide an appropriate model fit. External trip attractions and productions (in-commuting flows) is another significant variable in this research, especially in analyzing traffic crashes at peak hours [47].

The geography of crashes is another factor associated with traffic safety, as a fixed effect that accounts for miscellaneous factors that are hard to measure and validate individually. Studies have shown that the geographic region can be considered as a group variable (control variable) along with injury severity, crash type and occupant type [69]. However, defining the geographical characteristics at the macro level has been questioned by some researchers. The spatial analysis of traffic crashes has such importance that some geographers believe that “geographic analysis is an alternative approach to the study of traffic accidents and their causes” [70]. Geographical regions can be an appropriate benchmark to measure the spatial and geographical similarities among UAs. In addition to geographic characteristics, weather condition also affects traffic safety [71]. Weather condition can be generally measured by average annual precipitation at the macro level. There is considerable research indicating that precipitation is associated with a significant increase in traffic crashes [72, 73]. These spatial characteristics can also be considered as trip attraction features since the weather and geographic specifications can positively affect trip generation by increasing the trip attraction.

2.4. Traffic Safety and Other Macro-Level Characteristics

As mentioned earlier, transportation-related characteristics are reported as the most significant variables in the body of traffic safety literature. Traffic flow variables (e.g., traffic congestion), roadway condition (e.g., road surface condition) and transportation network features (e.g., the share of transportation modes) are three major parts of transportation network characteristics. These attributes can directly and indirectly impact traffic crashes at both the micro- and macro-level. The relationship between some of these macro-level characteristics and traffic safety is reviewed in this section.

Although city-level transportation network characteristics are highly dependent on the structure of the UA, such as the distribution of the population and employment in the UA, the size of the UA and the roadway network, the transit network in the UA is shown to be as significant as other macro-level variables in the traffic safety literature [33]. In this respect, several metrics of transit supply exist, including both bus route miles and rail route miles in UAs [33]. Transit availability is another measure of the transportation network.

This parameter is defined as the proximity to public transit which is generally defined as the average distance of households to the nearest transit stop [33]. Transit availability is expected to alter travel behavior, and consequently influence traffic safety [74].

In addition to transit availability, the share of other transportation modes, such as car, bike, taxi and walking, is a crucial factor in both transportation planning and safety policy development. Different modes of transportation have different exposures to the risk of traffic crashes. For instance, the risk of crashes for pedestrians who have to cross an unsignalized intersection is higher than for other users of a transportation network [75]. In addition, the commute mode choice, as a main paradigm of transportation networks, is strongly influenced by urban form characteristics (e.g., distribution of employment, distribution of services, pattern of residential land-uses, and the density of roadways) [33]. Thus, the transportation mode share is directly and indirectly correlated with traffic safety. Not only is the transportation mode important, but also the share of different vehicle configurations is important to traffic safety considerations. The percentage of heavy vehicles, Single Occupancy Vehicles (SOVs) and High Occupancy Vehicles (HOVs) is an important factor in determining traffic behavior on the roadways. The risk of fatal crashes is higher for HOVs since a higher number of passengers are involved in each crash. However, at a broader picture, the risk of fatal crashes increases with an increase in the share of SOVs rather than HOVs, as the number of vehicles (VMT) and therefore the probability of exposure to the risk of traffic crashes increase. Heavy vehicles are also associated with a higher rate of fatal crashes since the presence of heavy vehicles in a traffic crash increases its injury severity [76].

Street network density, network connectivity and street network pattern, as three main transportation network characteristics, are shown to be correlated with traffic safety outcomes by Marshall and Garrick [77]. Denser transportation networks with a higher number of intersections are associated with fewer crashes. It is suggested that in addition to traffic flow and roadway characteristics, transportation network layout (such as patterns and street designs) affect crash frequency and severity [77]. Ewing and Dumbaugh [38] reviewed the effect of the built environment on traffic safety and concluded that “the traffic environments of dense UAs appear to be safer than the lower-volume environments of the suburbs.” They introduced shorter driving distance and lower speeds as two main reasons for this situation. Cottrill et al. [78] presents the level of accessibility to transit as the other effective factor on traffic safety along with different network characteristics.

In summary, transportation network layout, structure, density and connectivity along with the network type (e.g., the share of freeway vs local road miles) are strongly correlated with many aspects of transportation planning, including traffic safety. Another important characteristic of a transportation network is the duration and intensity (PHF, Peak-Hour Factor) of peak periods, since the traffic behavior is different during peak periods than off peaks [79]. Commuting departure time and commuting travel time [80] can be two exploratory variables for peak periods at the macro level.

The relationship between traffic flow and safety may not be straightforward as it may be masked by many traffic related variables, such as traffic congestion and traffic speed. One can generally expect that average traffic speed is relatively low on congested roadways which may result in a lower crash severity and a lower frequency of crashes [81]. Golob et al. [82] presented evidence for a strong relationship between traffic flow conditions and crash probability. They suggested the basis for a tool that monitors the level of safety based on traffic congestion. However, the main challenge is to define traffic flow characteristics at the macro level and study the effect of aggregate traffic congestion on traffic safety.

Roadway characteristics and vehicle characteristics are other factors potentially affecting traffic safety. This research focuses on roadway condition (i.e., pavement condition) as the only representation of roadway characteristics, since many other aggregate and high-level roadway features are already implicitly considered through the transportation network characteristics [83]. However, vehicle characteristics are not studied at all due to data availability issues. Tighe et al. [84] proposed a systematic approach for the coordination of pavement maintenance with road safety improvement programs, trying to incorporate and integrate traffic safety management with pavement management systems. They also recommended a list of possible remedial measures for traffic safety improvements associated with pavement maintenance activities. Mayora and Pina [85] analyzed the influence of pavement condition and also improving pavement friction on traffic safety. The results confirmed the potential of pavement friction improvement on traffic crash reduction.

In summary, one can divide transportation-related characteristics with anticipated effect on urban planning and traffic safety into three major categories, namely transportation network features, traffic flow characteristics and roadway conditions.

2.5. Pedestrian Safety and Urban Characteristics

Walking is the most traditional form of transportation, the most common physical activity and the final necessary step to access public places for all types of transportation network's users [86]. However, walking has the highest risk of injury or death amongst all transportation modes [87]. while, the main traditional focus of transportation planners has been on improving the safety of traffic on the roadways for motor vehicles, not for the pedestrians, traffic safety planners have recently given more attention to pedestrian safety [88, 89]. This is a critical responsibility for transportation planners to provide both safety and efficiency for all users of transportation network, especially when it comes to the conflicting needs of motorists and pedestrians. For instance, providing efficient and safe timing for a traffic signal where efficiency is needed to reduce the delay of vehicles and safety is required for pedestrians who have conflicting movements with those of vehicles [90].

To review the pedestrian safety literature [88], we first need to address some basic questions: "When do pedestrian crashes occur? Who is involved in pedestrian crashes? Where do pedestrian crashes occur? How do pedestrian crashes occur?" Different types of pedestrian crashes occur at different times of the day, days of the week and according to the season. Most fatal pedestrian crashes occur in nighttime while non-fatal pedestrian crashes mostly occur during the daytime. Generally, pedestrian crashes are more frequently on Fridays and Saturdays compared to Sundays. Adult pedestrian crashes occur more frequent in the winter and child pedestrian crashes are more likely occur in the summer. The rate of pedestrian crashes across different age groups in the population is higher among children and young adults (2-22 years old users). Male pedestrians are generally more involved in crashes compared to females, regardless of the age group. About 60 percent of fatal pedestrian crashes result from pedestrian alcohol-related behaviors. There is research showing that intoxicated pedestrians are even more dangerous than drunken drivers. Heavy vehicles are also associated with a higher rate of pedestrian crashes compared to other types of vehicles. In UAs, pedestrian crashes are more likely associated with driver violations at intersections compared to non-pedestrian crashes. Seventy-four percent of pedestrian crashes in UAs occur where there is no traffic control (neither signal nor stop sign). Most pedestrian crashes occur on roadways of lower functional class with lower speed limits. There are many significant factors contributing to pedestrian crashes, however avoiding only one of them would not result in a very significant improvement in the overall pedestrian safety [88].

Some research has been done on various aspects of pedestrian crashes at the micro-level, trying to identify significant characteristics involved in pedestrian fatalities. Some of the effective micro-level countermeasures are summarized as follows [88, 91]:

- Improving visibility between motor vehicles and pedestrians
- Raised medians on multilane roadways
- Improving nighttime lighting
- Provision of an exclusive pedestrian interval in traffic signal timing (which reduces the incidence of pedestrian crashes by 50 percent)
- Reducing conflicts between pedestrians and vehicles by using warning signs (e.g., “yield to pedestrians when turning” sign, “pedestrians watch for turning vehicles” sign and “walk with care” sign)
- Reducing vehicles speed at pedestrian crossways by using traffic devices
- Providing specific facilities for pedestrians with disabilities (e.g., textured pavements, audible and vibrating pedestrian signals and wheelchair ramps)
- Replacement of bus stops considering the pedestrian safety requirements
- Appropriate police enforcement

- Proper signalization and the provision of enhanced sidewalks for students
- Improving sidewalks and walkways in general
- Micro-level traffic calming measures (e.g., street closures, speed humps, series of alternating curb extensions, traffic curbs and diverters)

In addition to micro-level characteristics, macro-level (city-level) characteristics of traffic flow, transportation network and urban form are associated with pedestrian safety [92]. Certain characteristics of urban form not only encourage walking as a mode of transportation, but also increase the safety of pedestrians [93]. Research shows that the level of assigned funding for pedestrian-oriented policies (e.g., pedestrian-friendly urban design and sustainable land-use planning regulations and practices) will result in an increase in pedestrian safety. Higher pedestrian safety will then give pedestrians a higher motivation to walk, which improves public fitness as well [94].

Collaborative research between transportation and urban design is a new trend in public health to assure pedestrian safety. Considering these three elements (transportation, urban form and pedestrian safety) as essential integrated parts of urban planning that all have similar objectives, key urban design features to engage pedestrians have been introduced as follows: density, accessibility, street connectivity and mixed land-use. "Restricting city blocks to pedestrian only access, placing car parks away from building entrances, and making stairways more accessible and convenient" are some instances of this collaborative concept to provide safe and efficient physical activity [86]. Studies indicate that walking is a safer mode of transportation in European cities than other industrialized non-European cities because of appropriate design based on pedestrians' needs, traffic education policies, automobile restriction policies and traffic calming [86].

Many studies have shown that mixed land-use is the most significant urban characteristic to affect the walkability in the UA by providing accessibility to various destinations and convenience for local users [86]. Population is one of the macro-level urban characteristics associated with pedestrian safety. In large UAs with higher population, the incidence of pedestrian fatalities and casualties increases as a result of increased traffic volume, especially in residential areas compared to business zones. Urban density (population density and employment density) is another important macro-level urban characteristic. The frequency and probability of pedestrian crashes decreases with an increase in population density mostly due to the supply of pedestrian facilities, speed restriction and traffic management measures. On the other hand, there is a nonlinear relationship between employment density and the rate of pedestrian crashes. Increased employment density increases the incidence of pedestrian crashes in all types of areas except extremely dense economic areas [95].

Traffic calming is the other macro-level factor that helps increasing pedestrian safety in UAs. Traffic calming is basically "the combination of mainly physical measures that reduce the negative effects of motor vehicle use, alter driver behavior and improve conditions for non-vehicular traffic", such as street restriction policies, using traffic circles, providing pedestrian crossings, speed limit control, speed watch and enforcement programs, and parking controls [86].

In addition to all the aforementioned factors, research shows that most driver errors in UAs are not a personal random mistake, but rather the characteristics of the built environment can be the main source of these errors. It is also worth mentioning that the factors effective on a vehicle-to-pedestrian crash are most likely the same as the factors associated with a vehicle-to-vehicle crash. This indicates that urban characteristics (built environment) have a major role in traffic safety issues, specifically pedestrian crashes [96].

2.6. Conclusions

2.6.1. Summary

In this section, the lessons learned from the literature are briefly summarized.

1- Different characteristics of a UA, as a complex socio-physical system, should be considered in traffic safety planning, including city characteristics, household characteristics, traffic flow, transportation network characteristics and roadway condition.

2- Urban form is generally defined in three different levels (street-, community- and city-level). Although, the first two disaggregate-level definitions are well-studied, there is a gap in the traffic safety literature that focuses on the effective factors of macro-level urban on traffic safety. This research contributes to the traffic safety literature by defining the factors of macro-level urban form and studying their significance in traffic safety modeling.

3- Trip generation is a vital element of traffic safety planning, as it is the first step of transportation modeling and necessary to estimate traffic flow information on roadways. Trip production characteristics (e.g., population size, population density, employment, household income and GDP) and trip attraction characteristics (e.g., trip attraction centers, such as restaurants and grocery stores, job centers, and geographic characteristics) are two components of trip generation.

4- Traffic flow characteristics (e.g., traffic congestion), roadway condition (e.g., road surface condition) and transportation network characteristics (e.g., public transit availability, network type, network connectivity and density) are the major transportation-related features studied in association with traffic safety.

5- Pedestrian safety, especially in UAs, is a complementary concept along with general traffic safety since pedestrian fatalities comprise about 15 percent of overall traffic fatalities. Research has suggested several micro-level practices to decrease the incidence of pedestrian crashes, however this research tries to determine most significant aggregate-level urban characteristics to increase pedestrian safety.

2.6.2. Limitations

The main limitations of previous studies are summarized as follows:

- There is rather limited macro-level research on traffic safety at the city level that considers urban features. The present research studies UAs using city-level variables.
- There are no integrated and comprehensive studies that focus on urban features and transportation-related characteristics at the same time. This study tries to develop a comprehensive framework for traffic safety in UAs, considering urban features in addition to transportation related characteristics.
- There has been no research to compare the effect of urban characteristics on pedestrian safety to the effects on overall traffic safety. This research focuses on pedestrian safety separately and makes recommendations to improve pedestrian safety in addition to the overall traffic safety in UAs.
- Data availability: data is the major limitation for many research undertakings. This study is influenced by data limitation as well, since information for only 100 US cities are available.

CHAPTER 3: DATA DESCRIPTION

3.1. Introduction

This chapter introduces the data used in this research and explains how the data is collected, defined, manipulated, managed and finally categorized for the purpose of this research. The scope of the research, studied variables, their characteristics and different sources of the data are explained in this chapter. The year 2010 is considered as the base year of this study, because of data availability (e.g., crash database, population census, etc.). Although 2010 is the target of data collection, there are a few instances where 2010 data is not available. In these situations, the closest existing temporal information is used. It is expected that the substitute data can satisfactory approximate the 2010 data since variables are mostly defined in per capita ratio form (i.e., values divided by population). Although many measures change over time, most of them show less variation in the form of per capita ratio.

3.2. Scope of Research

The Urban Mobility Report (UMR) [97] identifies 498 UAs in the United States. Due to various considerations and due to data availability (explained in the next section), 100 UAs in the United States are studied in this research. This set of UAs can be grouped by population into four groups: very large (population over 3 million), large (1 to 3 million), medium (500,000 to 1 million), and small (under 500,000). This set of 100 UAs is not a random sample, but a convenience sample that is top heavy. All the very large (15

UAs) and large UAs (31 UAs) are included in this dataset, as well as 33 out of 36 mid-size UAs (92%), and 21 out of 415 small UAs (5%). Since safety is more of an issue in larger cities, it is important to oversample among larger cities in the interest of representativeness, and in the interest of stronger policy relevance.

Table 3.1 displays these 100 UAs grouped by UMR size category, sorted within each group by population. In this table, traffic safety metrics (safety performance measures), including number of fatal crashes per 100,000 population (FCRA), number of fatalities per 100,000 population (FATA), number of vehicles involved in fatal crashes per 100,000 population (FVEH), and number of pedestrians involved in fatal crashes per 100,000 population (FPED), are shaded based on the quartile of each UA, with darker shades indicating higher rates and higher quartiles. Using fatal crash rate as a metric of traffic safety produces an implicit compounding bias in the response variable, since the number of fatal crashes is highly dependent on the population size. Instead, dependent variables are well-behaved statistically when they are defined as rates of fatal crashes per 100,000 people. Using rates instead of frequencies is one of the main assumptions in this study for several other variables as well, since it removes the strong effect of population size on a variety of urban characteristics.

TABLE 3.1: Urban areas sorted by size category - traffic safety measures

Urban Area	FCRA	FATA	FVEH	FPED
Very Large Urban Areas				
New York-Newark	3.40	3.50	4.85	2.39
Los Angeles-L. Beach-S. Ana	5.67	5.99	9.35	3.10
Chicago	4.70	5.20	7.30	1.50
Miami	7.98	8.79	11.73	3.16
Philadelphia	5.50	6.10	9.00	23.00
Dallas-Fort Worth-Arlington	8.45	9.30	13.72	1.85
Washington	4.00	4.00	5.20	2.70
Atlanta	10.20	11.20	15.70	4.00
Boston	2.90	2.90	3.70	1.90
San Francisco-Oakland	4.61	4.98	7.45	2.17
Houston	9.70	10.30	14.70	2.80
Detroit	12.30	13.00	18.10	3.50
Phoenix-Mesa	8.31	9.16	13.52	3.60
Seattle	3.80	4.10	5.90	1.60
San Diego	5.00	5.60	8.10	2.10
Large Urban Areas				
Minneapolis-St. Paul	3.01	3.76	5.15	1.33
Baltimore	6.00	6.30	8.70	2.10
Tampa-St. Petersburg	13.09	14.11	21.53	5.23
St. Louis	13.20	13.80	21.60	3.80
Denver-Aurora	4.86	5.45	8.88	1.49
Riverside-San Bernardino	7.20	7.77	10.66	1.92
Portland	3.90	4.10	6.00	3.30
Sacramento	9.72	10.26	13.82	5.20
San Jose	3.60	3.80	6.70	1.00
Pittsburgh	7.50	8.80	10.80	2.60
Cincinnati	4.40	4.40	7.10	0.70
Cleveland	8.10	8.80	11.80	1.80
Kansas City	12.59	13.58	20.64	1.48
Virginia Beach	4.10	4.30	6.60	1.10
San Antonio	8.30	9.10	12.60	2.50
Milwaukee	8.10	8.70	13.10	2.90
Orlando	9.70	10.10	15.90	3.40
Las Vegas	4.50	4.97	6.77	1.62
Austin	6.20	6.50	10.10	1.50
Columbus	6.40	6.50	10.90	1.80
Providence	5.43	5.43	8.12	3.09
Indianapolis	8.30	8.50	13.40	2.60
Nashville-Davidson	10.30	10.60	15.00	2.20
Raleigh-Durham	6.81	6.81	11.21	1.56
Louisville	9.00	9.39	13.96	2.91
Jacksonville	12.40	13.00	18.40	3.30
Charlotte	5.70	5.70	8.30	2.60
Memphis	11.00	11.40	16.40	2.20
New Orleans	7.30	7.90	10.50	1.20
Buffalo	4.60	4.60	7.30	0.40
Salt Lake City	8.60	8.60	13.40	2.10

Urban Area	FCRA	FATA	FVEH	FPED
Medium Urban Areas				
Oklahoma City	12.10	12.90	20.00	3.60
Richmond	6.40	6.40	10.30	1.50
Bridgeport-Stamford	5.59	5.59	7.89	0.74
Hartford	10.40	12.00	17.60	3.20
Birmingham	12.70	13.70	19.30	1.90
Rochester	8.10	10.00	10.00	2.40
Dayton	9.20	10.60	13.40	0.70
El Paso	7.90	8.00	11.10	1.80
Honolulu	6.40	6.40	8.30	3.70
Tucson	11.00	11.50	17.50	2.70
Tulsa	11.00	11.50	17.10	1.80
Oxnard	2.00	2.50	2.50	1.00
Fresno	5.50	7.10	8.90	3.40
Sarasota-Bradenton	15.82	16.78	26.65	6.91
Omaha	4.90	5.10	8.10	1.50
Allentown-Bethlehem	5.72	5.72	10.39	0.99
Springfield	1.30	3.30	5.20	2.00
Albuquerque	6.60	7.30	10.40	2.20
Akron	5.50	5.50	7.50	1.00
New Haven	10.00	10.80	15.40	2.30
Albany	3.10	3.10	4.10	1.00
Grand Rapids	6.40	6.90	9.00	2.70
Baton Rouge	13.50	14.40	22.20	4.40
Lancaster-Palmdale	4.81	4.86	6.76	2.30
Indio-Cath City-Palm Springs	14.43	14.98	21.93	5.15
McAllen	3.90	3.90	8.50	1.50
Colorado Springs	4.60	4.80	7.20	0.70
Poughkeepsie-Newburgh	5.01	5.01	8.33	1.69
Bakersfield	6.60	6.90	10.60	2.90
Charleston-N. Charleston	12.85	12.85	16.06	6.91
Toledo	9.10	10.80	13.20	2.40
Wichita	7.60	7.80	14.40	1.00
Knoxville	16.80	17.30	24.00	2.20
Small Urban Areas				
Columbia	7.00	7.00	11.60	3.10
Provo-Orem	2.52	2.52	3.51	1.49
Cape Coral	6.50	6.50	7.80	3.90
Little Rock	13.78	14.18	21.24	2.75
Worcester	5.00	6.10	7.70	0.60
Jackson	12.70	13.30	17.30	2.90
Stockton	3.80	9.60	13.40	4.10
Madison	4.70	4.70	7.30	1.70
Winston-Salem	6.10	6.50	8.70	2.60
Spokane	3.80	3.80	6.70	1.40
Pensacola	1.90	1.90	1.90	0.00
Greensboro	8.90	10.00	15.90	2.20
Corpus Christi	5.90	5.90	7.90	2.60
Boise	3.40	3.40	4.90	0.50
Anchorage	3.40	3.40	4.80	1.00
Eugene	3.80	3.80	3.80	2.60
Salem	1.30	5.20	7.10	1.90
Beaumont	11.80	11.80	18.60	1.70
Laredo	5.90	6.40	7.60	2.50
Brownsville	8.00	8.00	12.60	4.00
Boulder	1.00	1.00	2.10	0.00

Averages

Legend		FCRA	FATA	FVEH	FPED
Top Quartile	Very Large Urban Areas	6.43	6.94	9.89	3.96
2nd Quartile	Large Urban Areas	7.55	7.97	11.79	2.29
3rd Quartile	Mid-size Urban Areas	8.09	8.68	12.54	2.43
Bottom Quartile	Small Urban Areas	5.77	6.43	9.16	2.07

Figure 3.1 shows the geographic location of these 100 UAs, divided into 5 groups based on the FCRA ratio (i.e., number of fatal crashes per 100,000 population): 1-3, 3-5,

5-8, 8-11 and 11-17. Darker shades indicate higher rates.

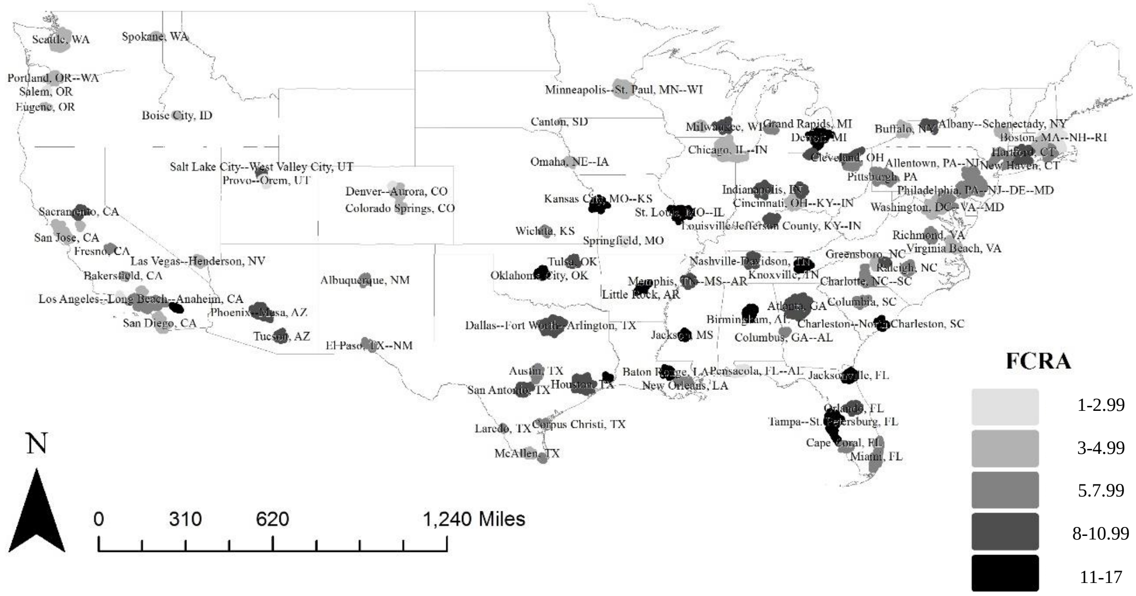

FIGURE 3.1: Urban areas and FCRA ratio.

As revealed by Table 3.1, different quartile shading colors show no noticeable pattern across groupings of UAs according to population. In other words, there is no strong obvious correlation between crash rate and city size. This broad variation among the studied cities is one of the main motivations to study the effect of other urban characteristics on traffic safety and crash rate. Considering the crash rate in Figure 3.1, UAs are spatially random distributed and there is no spatial pattern among studied UAs.

3.3. Studied Variables

Traffic safety indicators (safety performance measures), urban characteristics, household characteristics and transportation network characteristics are the four main categories of variables examined in this research.

3.3.1. Traffic Safety

Table 3.2 contains a list of traffic safety variables as well as their descriptions, units and descriptive statistics. The information for the year 2010 is used to assemble this part of the database. Fatal crashes are considered as the basis to specify the traffic safety variables because there is no other national-wide information on traffic accidents, such as traffic incidents or non-fatal traffic crashes. Although traffic crashes do not have a spatially uniform distribution within the UAs (i.e., some areas within a UA are more prone to traffic crashes than others), this research analyzes the macro-level traffic safety, which requires to study aggregate safety performance measures, and does not differentiate between different parts of a UA.

TABLE 3.2: Traffic safety variables, descriptions, units and statistics

Variable and Description	Unit	Acronym	Min	Mean	Max	St. D.
# of fatal crashes per 100K population	# of FatalCrash/100K-Pop	FCRA	1	7.184	16.8	3.477
# of fatalities per 100K population	# of Fatalities/100K-Pop	FATA	1	7.724	17.3	3.610
# of persons involved in fatal crashes per 100K population	# of Person/100K-Pop	FPER	3.1	16.339	40.1	8.148
# of vehicles involved in fatal crashes per 100K population	# of Veh/100K-Pop	FVEH	1.9	11.199	26.646	5.345
# of fatal crashes involving drunken drivers per 100K population	# of DrunkPerson/100K-Pop	FDRU	0	2.668	5.929	1.582
# of pedestrians involved in fatal crashes per 100K population	# of Ped/100K-Pop	FPED	0	2.540	23	2.414

Variables, data collection process and the source of data are described as follows:

- Number of fatal crashes per 100,000 population: this variable is a ratio (continuous variable) to represent the rate of fatal crashes in the UA, collected from City Data online website [98] and validated by Find the Home online website [99].
- Number of fatalities per 100,000 population: this variable is a ratio (continuous variable) to represent the rate of fatalities in the UA, collected from City Data online website [98] and validated by Find the Home online website [99].
- Number of persons involved in fatal crashes per 100,000 population: this variable is a ratio (continuous variable) to represent the rate of passengers of fatal crashes in the UA, collected from City Data online website [98] and validated by Find the Home online website [99].
- Number of vehicles involved in fatal crashes per 100,000 population: this variable is a ratio (continuous variable) to represent the rate of vehicles in fatal crashes in

the UA, collected from City Data online website [98] and validated by Find the Home online website [99].

- Number of fatal crashes involving drunken drivers per 100,000 population: this variable is a ratio (continuous variable) to represent the rate of drunk drivers of fatal crashes in the UA, collected from City Data online website [98] and validated by Find the Home online website [99].
- Number of pedestrians involved in fatal crashes per 100,000 population: this variable is a ratio (continuous variable) to represent the rate of pedestrians of fatal crashes in the UA, collected from City Data online website [98] and validated by Find the Home online website [99].

3.3.2. Urban Characteristics

Table 3.3 contains a list of urban characteristics as well as their descriptions, units and descriptive statistics. The information for the year 2010 is mainly used to assemble this part of database. However, the closest available time period is used for some variables (as reported in the table), when the 2010 data is not available.

TABLE 3.3: Urban characteristics, descriptions, units and statistics

Variable and Description	Unit	Acronym	Min	Mean	Max	St. D.
Population	#K-Population	POPS	150	1696.3	18852	2526.7
Area	Square Miles: SqMile	AREA	32.49	569.23	3450.2	579.45
Percentage change in population from 2000 to 2010	%	POPP	-5.495	17.663	71.212	12.967
Commuters per square mile	#/SqMile	COSM	602.53	1470.3	4531.3	713.97
Persons per square mile	#/SqMile	PRSM	1150.3	2875.9	8681.5	1436.5
Commuters + persons per square mile	#/SqMile	COPRSM	1752.8	4346.2	13213	2141.8
Income per capita in 2012*	$	INPC	13391	27378	46808	5398
Employment per capita in 2012*	Emp per capita	EMPC	0.349	0.465	0.566	0.041
Percent of employment in job-rich and job-dense tracts	%	EMJR	17.088	35.108	54.353	8.076
Percent of population in job-poor tracts	%	POJP	29.139	45.891	60.263	5.972
Gini coefficient of workers per population	Ratio	GIWP	0.056	0.104	0.156	0.019
Gini coefficient of employment density	Ratio	GIEM	0.432	0.641	0.785	0.068
Gini coefficient of jobs per households	Ratio	GIJH	0.442	0.658	0.892	0.103
Gini coefficient of jobs per workers	Ratio	GIJW	0.473	0.654	0.882	0.089
Gini coefficient of car ownership per households	Ratio	GICO	0.077	0.131	0.321	0.032
Gini coefficient of households' median income	Ratio	GIMI	0.163	0.231	0.346	0.034
Restaurants per 10K population	#/10K-Pop	REPC	18.349	32.906	54.659	8.461
Cafes per 10K population	#/10K-Pop	CAPC	3.323	7.389	17.87	2.727
Bars per 10K population	#/10K-Pop	BAPC	0.882	5.928	13.282	2.452
Religious organizations per 10K population	#/10K-Pop	ROPC	6.270	20.882	43.573	7.852
Fitness centers per 10K population	#/10K-Pop	FCPC	1.104	2.926	9.561	1.336
Yoga studios per 10K population	#/10K-Pop	YSPC	0.065	0.599	4.382	0.589
Vice per 10K population	#/10K-Pop	VIPC	0.392	3.204	8.393	1.107
Alternate medicine per 10K population	#/10K-Pop	AMPC	0.050	0.817	9.063	1.165
Number of professional sport teams per capita	#/1,000K-Pop	STPC	0	3.393	9.542	1.918
In-commuting flows per worker ((Jobs in UA tracts - Workers in UA tracts)*100 / Workers in UA tracts)	%	COFW	-21.43	5.507	54.486	9.232
Political party control in 2000	Binary: 1=Dem, 0=Rep	POLP	0	0.69	1	0.462
City age: number of decades before 2010 that city has reached 50k in population	#	CAGE	0	9.83	21	4.318
Dummy variable based on UA population (Small)	Binary: 1=Small, 0=Others	CSZ1	0	0.21	1	0.407
Dummy variable based on UA population (Medium)	Binary: 1=Medium, 0=Others	CSZ2	0	0.33	1	0.470
Dummy variable based on UA population (Large)	Binary: 1=Large, 0=Others	CSZ3	0	0.31	1	0.462
Dummy variable based on UA population (Very Large)	Binary: 1=Very Large, 0=Others	CSZ4	0	0.15	1	0.357
Dummy variable based on UA geography (South)	Binary: 1=South, 0=Others	CGE1	0	0.39	1	0.488
Dummy variable based on UA geography (Northeast)	Binary: 1=Northeast, 0=Others	CGE2	0	0.15	1	0.357
Dummy variable based on UA geography (Midwest)	Binary: 1=Midwest, 0=Others	CGE3	0	0.17	1	0.376
Dummy variable based on UA geography (West)	Binary: 1=West, 0=Others	CGE4	0	0.29	1	0.454
Annual precipitation	Inches	ANPE	5.9	35.127	65.1	13.956
Median housing cost per median household income	$/$	HOCO	2.025	3.515	8.455	1.136
Percent of employees working for government in 2012*	%	EMGO	8.477	14.598	23.263	3.803
Percent of employment in retail in 2012*	%	EMRE	8.258	11.857	16.848	1.355
The ratio of retail employment to governmental employment	Ratio	RETGO	0.35	0.86	1.42	0.23
Patents per K-workers	#/K-Workers	PAPW	0.019	0.955	10.291	1.291
Real GDP per VMT	TotalGDP/VMT	GDPP	2.033	5.347	14.524	2.265
Officers per K-residents	#/K-Residents	OFFP	0.895	2.336	6.12	0.962
Grocery stores per 10K population	#/10K-Pop	GRST	0.84	2.053	7.038	0.795
Club stores per 10K population	#/10K-Pop	CLST	0	0.109	0.44	0.073
Convenience stores no gas per 10K population	#/10K-Pop	NGST	0.059	0.982	2.68	0.537
Convenience stores with gas per 10K population	#/10K-Pop	WGST	0.148	2.7082	5.77	1.027
Sum of all type of grocery stores (GRST+CLST+NGST+WGST)	#/10K-Pop	GSTOR	2.77	5.85	9.95	1.30
Full service restaurants per 10K population	#/10K-Pop	FRES	2.84	7.7462	23.781	2.586
Monthly rent <$500	%	MRE1	0.7	17.839	52.7	12.960
Monthly rent: $500-$1000	%	MRE2	13.4	58.632	85.2	14.048
Monthly rent: $1000-$1500	%	MRE3	0.3	14.440	50.5	10.112
Monthly rent: >$1500	%	MRE4	0	9.099	52.7	10.163
Average monthly rent	$	MRENT	496	824	1417	189
Energy use: utility gas	%	UGAS	0.7	55.235	90.6	23.771
Energy use: electricity	%	ELEC	6.65	38.726	97.62	24.289
Energy use: oil	%	OILG	0	2.930	27.188	6.340
Energy use: LP gas/bottled/tank	%	LPGA	0.12	0.986	3.213	0.442
Energy use: coal/coke	%	COAL	0	0.021	0.28	0.043
Energy use: wood	%	WOOD	0	0.298	2.75	0.423
Energy use: solar	%	SOLA	0	0.035	1	0.113
Energy use: other	%	OFUE	0	0.280	1.357	0.283
No energy	%	NFUE	0.072	1.483	56.82	5.899
Sum of renewable energies (ELEC+SOLA+OFUE+NFUE)	%	NFUEL	7.66	40.52	99.09	25.02

* 2012 data is used in some cases which is the closest estimation for the 2010 data.

Variables, data collection process and the source of data are described as follows:

- Population: this variable represents each UA's population and is collected from UMR [97] and validated by City Data online website [98] and Census data [7].
- Area: this variable represents each UA's area and is collected from Census data [7] and validated by City Data online website [98].
- Percentage change in population from 2000 to 2010: 2000 and 2010 population information are compared to determine the percent change of population in the UA. The population information is collected from UMR [97] and validated by City Data online website [98] and Census data [7].
- Commuters per square mile: this variable is a ratio to represent the number of commuters per square mile in the UA [54]. To calculate this variable, the number of commuters, from the UMR [97], is divided by UA square mileage from the Census data [7].
- Persons per square mile: this variable is a ratio to represent the number of residents (persons) per square mile in the UA [54]. To calculate this variable, the UA's population, from the UMR [97], is divided by UA square mileage from the Census data [7]. The sum of commuters and persons per square mile is also another studied variable in the dataset.
- Income per capita in 2012: this variable is a ratio to represent the average income per capita for the UA [54]. Income per capita is given in American Community Survey (ACS) for the year 2012 [100], which is the closest estimation for income per capita of 2010 [54].
- Employment per capita in 2012: this variable is a ratio to represent the number of employments per capita of the UA [54]. Employment information, given in

American Community survey (ACS), in the 2012 [100] (the closest estimation for employment per capita in 2010) is divided by the population data [54].

- Percent of employment in job-rich and job-dense tracts: this variable is a percentage value to represent the centrality of the UA [54]. Job rich tracts are the census tracts with at least twice as many jobs as workers. To determine the job-rich tracts, first the number of workers by the place of work is divided by the number of workers by the place of residence. Job-dense tracts are the census tracts with at least five times the average jobs per square mile. To determine the job-dense tracts, first the number of workers by the place of work is divided by the area of that tract. This ratio is then compared with the average employment density ratio. Finally, the cumulative number of jobs in the census tracts that are both job-rich and job-dense is compared to the total number of jobs in the entire UA [54]. Census data [7] is the main source for all of this information.
- Percent of population in job-poor tracts: job-poor tracts are the census tracts with at least twice as many workers as jobs. To determine the job-poor tracts, the number of workers by the place of work are compared to the number of workers by the place of residence, determined from the Census data [7, 54]. The cumulative population in job-poor census tracts is finally compared to the total population in the UA.
- Gini[1] coefficient of workers per population: this variable is a ratio to represent the

[1] The Gini coefficient is a dimensionless measure accounting for statistical dispersion to access the even distribution of variables income and wealth. It represents the variations across census tracts within the UA. This variation is resulted from an unequal distribution of the variable in the UA. Variance, standard deviation and Gini coefficient are three common measures that account for the variation around the mean. Generally, small variance and small standard deviation indicate that the dispersion of the variable is around the mean value. Variance values are relative and might be different for different samples or variables. To overcome this drawback, Gini coefficient is introduced. The coefficient varies from 0 to 1, with 0 indicating perfect

variation in the aggregate number of workers per capita within the UA [54]. To calculate the Gini coefficient of workers per population, first the aggregate number of workers of each census tract is divided by the population of that census tracts. These ratios are then compared across all census tracts of the UA to show the variation of workers per population within the UA [7, 54].

- Gini coefficient of employment density: this variable is a ratio to represent the variation in the employment density within the UA [54]. To calculate the Gini coefficient of employment density for the UA, first the number of workers in each census tract, from the Census data [7], is divided by the area of that census tract, determined from the TransCAD census tract layer [54, 101]. These ratios are then compared across all census tracts of the UA to show the variation of employment density within the UA.
- Gini coefficient of jobs per households: this variable is a ratio to represent the variation in the number of jobs per household within the UA [54]. To calculate the Gini coefficient of jobs per household for the UA, first the number of workers in each census tract, from the Census data [7], is divided by the number of households in that census tract. These ratios are then compared across all census tracts of the UA to show the variation of jobs density within the UA [54].
- Gini coefficient of jobs per workers: this variable is a ratio to represent the variation in the number of jobs per number of workers within the UA [54]. To calculate the Gini coefficient of jobs per workers for the UA, first the number of workers (by place of work) in each census tract, from the Census data [7], is divided by the

evenness (all samples have equal shares) and 1 indicating a perfect inequality (one sample has all the share) [53].

number of workers (by place of residence) in that census tract. These ratios are then compared across all census tracts of the UA to show the variation of jobs per workers within the UA [54].

- Gini coefficient of car ownership: this variable is a ratio to represent the variation in the average number of vehicles per each household within the UA [54]. The information for all census tracts inside each UA (the numbers of tracts in UAs vary from 4,454 in New York to 32 in Boulder), given by Census data [7], is used to calculate the Gini index for the UA [54]. To calculate the Gini coefficient of car ownership, first the aggregate number of vehicles in each census tract is divided by the aggregate number of households in that census tract. These ratios are then compared across all census tracts of the UA to show the variation of car ownership within the UA [7, 54].
- Gini coefficient of households' median income: this variable is a ratio to represent the variation in the median income of households within the UA [54]. To calculate the Gini coefficient of households' median income for the UA, first the median income of households in each census tract in the UA is calculated. These values are then compared across all census tracts of the UA to show the variation of household income within the UA [7, 54].
- Restaurants, cafes, bars, religious organizations, fitness centers and yoga studios per 10,000 population: these ratios represent the number of restaurants, cafes, bars, religious organizations, fitness centers and yoga studios per 10,000 population for the UA, collected from Find the Home online website [99] and validated by City Data online website [98].

- Vice per 10,000 population: this variable is a ratio to represent the number of casinos, liquor stores, and adult entertainment establishments per 10,000 population for the UA, collected from Find the Home online website [99].
- Alternate medicine centers per 10,000 population: this variable is a ratio to represent the number of businesses that practice alternative medicine (e.g., acupuncture, serve to heal or treat diseases with methods other than those typically associated with western medicine) per 10,000 population for the UA, collected from Find the Home online website [99].
- Number of professional sport teams and/or NCAA Division I colleges per capita: this variable is a ratio to represent the number of upper-level sports teams per 1,000,000 population in the UA [54] and is an estimator for the number of special events. The data is gathered from 50States.com website, city websites, lists of professional sports teams and NCAA Division I institutions in Wikipedia [54].
- In-commuting flows per worker: this variable is a ratio ((number of jobs in UA – number of workers in UA)×100 / number of workers in UA) to represent the percent of in-commuting flows per workers. If the number of jobs in the UA is greater than the number of workers in the UA, there is a daily attracted flow of workers from the outside into the UA. The number of workers and jobs in the UA census tracts are coming from the Census data [7] to determine the net flow into the UA from the hinterlands. The main assumption of this variable is that each worker can only have one job at most [54].
- Political party control in 2000: this is a binary variable (1 represents democrats and 0 represents republicans) to represent the political affiliation of mayor in 2000. This

variable is used to address the effect of long-term planning. It is worth mentioning that "republicans tend to favor adding capacity to the street/highway network to allow people to follow their revealed preference for the automobile, while Democrats tend to favor the other modes in a bid to improve the sustainability of the UA" [54]. Several different sources such as city websites, individual sites, World Statesmen website [102] and newspaper sites are reviewed to determine the political affiliation of mayor in 2000 [54].

- City age: this is a countable variable to represent the number of decades before 2010 that city has reached 50,000 in population. Many different sources such as Census data and city websites are used to determine the year when the UA reached a population of 50,000 [54].
- City Size: this is a set of dummy variables to represent the size of the UA based on the population [54]. Small, medium, large and very large are the categories of city size variable, coming from the UMR [97].
- Geographic region: this is a set of dummy variables to represent the geographic region of the UA based on the UA's location [54]. South, Northeast, Midwest, and West are the categories of this variable, determined from the Census data [7].
- Annual precipitation: this variable represents the average weather condition. 2010 Annual Climatological Summaries published by the National Climate Data Center [103] and the weather channel were used to collect and validate the annual precipitation data [54].
- Housing affordability: this variable is a ratio to represent median housing cost per median household income in the UA [54]. The Annual Demographic International

Housing Affordability Survey [104] is the source for this information.

- Percent of employees working for government in 2012: this is a percentage value to represent the ratio of employees that work for local government [54]. UA class of worker data in the ACS 2012 [100] is the main source for this information. This is the closest available estimation for the same variable in 2010.
- Percent of employment in retail in 2012: this is a percentage value to represent the ratio of employees that work for local retail [54]. UA class of worker data in the ACS 2012 [100] is the main source for this information. This is the closest available estimation for the same variable in 2010.
- The ratio of retail employment to governmental employment: this variable is a ratio of two aforementioned variables.
- Patents per 1,000 workers: this variable represents the number of patents per 1,000 workers in the UA. Brookings Institution [105] and City Data website [98] are the sources for this information. This variable can be a proxy for productivity.
- Real GDP per VMT: this variable is a ratio to represent the productivity (i.e., Gross Domestic Production; GDP) per Vehicle-Miles Traveled (VMT) [54]. The GDP per capita is reported by the Bureau of Economic Analysis [106] and the VMT is reported in Federal Highway Administration (FHWA) Highway Statistics [107]. To calculate this variable, the GDP per capita is multiplied by the population and then divide by the annual VMT [54]. It is worth mentioning that there are two missing values for this variable, both for mid-sized cities. A linear regression model with a high goodness of fit (R-Squared) was developed and validated to estimate the real GDP value for those 2 missing UAs.

- Officers per 1,000 residents: this variable represents the number of police officers per 1,000 populations in the UA. City Data online website [98] is the source for this variable.
- Food environment statistic: this is a set of variables to represent the number of grocery stores, club stores, convenience stores without gas, convenience stores with gas and full service restaurants per 10,000 populations in the UA. City Data online website [98] is the source for this variable. The total number of grocery stores is also another studied variable.
- Monthly rent: this is an ordinal variable with 4 categories (i.e., <$500, $500-$1000, $1000-$1500, and >$1500) to represent the average categorical monthly rent prices in the UA. Find the Home online website [99] is the source for this information. MRENT also represents the average rental cost in UAs.
- Energy type: this is a nominal variable with 10 categories (i.e., utility gas, electricity, oil, LP, gas/bottled/tank, coal/coke, wood, solar, other, no energy, and sum of renewable energy) to represent the average percentage share of each energy type in the UA. Find the Home online website [99] is the source for this information. Sum of the renewable energy can be a proxy for sustainability in UA.

3.3.3. Household Characteristics

Table 3.4 contains a list of household characteristics variables as well as their descriptions, units and descriptive statistics. The information for the year 2010 is used to assemble this part of the database.

TABLE 3.4: Household characteristics, descriptions, units and statistics

Variable and Description	Unit	Acronym	Min	Mean	Max	St. D.
Age <20	%	AGE1	18.088	26.915	38.140	3.647
Age: 20-24	%	AGE2	4.800	9.164	20.621	2.569
Age: 25-34	%	AGE3	10.520	16.161	21.540	2.255
Age: 35-44	%	AGE4	7.960	12.852	16.360	1.341
Age: 45-64	%	AGE5	13.551	23.546	28.820	2.232
Age >65	%	AGE6	7.081	11.367	22.966	2.341
The average age in UA	#	AAGE	28.74	35.60	42.11	1.92
Race: Hispanic	%	HISP	1.8	23.199	95.5	21.357
Race: White	%	WHIT	3.6	45.161	84.2	18.562
Race: Asian	%	ASI2	0.3	5.179	50.1	6.586
Race: Black	%	BLAC	0.1	23.072	83.0	19.072
Race: Indian	%	INDI	0.02	0.480	6.3	0.858
Race: Others	%	OTHR	0	2.909	20.97	2.324
Non-locals (born outside the UA)	%	FORC	1.9	14.644	53.501	9.402
Male	%	MALE	46.2	48.770	51.7	1.080
Female	%	FMAL	48.3	51.230	53.8	1.080
The ratio of male to female	%	MATFE	0.86	0.952	1.07	0.041
Language: English	%	ENGL	8.9	73.882	97.2	18.774
Language: Spanish	%	SPAN	1.4	18.064	90.5	18.134
Language: Asian	%	ASI3	0.2	3.831	33.8	4.903
Language: Indo/European	%	INDO	0.2	3.174	12.852	2.295
Language: others	%	OTHL	0	1.040	4.787	0.793
The percentage of non-English speakers (100-ENGL)	%	NOENG	2.8	26.11	91.1	18.77
Average household size	#	AHHS	2.1	2.518	4.0	0.352
Small family	%	SMFA	43.1	65.444	77.0	6.931
Medium family	%	MEFA	18.953	27.881	40.2	4.215
Large family	%	LAFA	1.8	6.674	19.4	3.089
Married	%	MARR	23.3	38.434	53.7	7.391
Never married	%	NMAR	24.8	41.631	58.7	7.421
Divorced	%	DIVO	6.068	11.569	15.851	2.153
Widowed	%	WIDO	2.784	5.583	9.95	1.143
Separated	%	SEPE	0.8	2.770	4.6	0.805
The percentage of non-married population (100-MARR)	%	NOMAR	46.3	61.565	76.7	7.390
Property- owner occupied	%	OWOC	24.1	51.215	71.0	7.844
Property- renter occupied	%	REOC	29.0	48.785	75.9	7.845
Annual household income <$25K	%	HHI1	11.8	29.795	48.2	7.064
Annual household income: $25K-$49K	%	HHI2	16.8	25.304	30.5	2.804
Annual household income: $50K-$75K	%	HHI3	12.6	16.865	21.6	1.700
Annual household income: $75K-$150K	%	HHI4	10.7	20.612	34.8	4.661
Annual household income >$150k	%	HHI5	1.6	7.428	22.6	3.929
Employed	%	EMPL	71.5	87.780	93.6	3.449
Unemployed	%	UEMP	5.2	11.504	28.5	3.421
Arm forces	%	ARMF	0	0.710	13.9	1.853
Education: no high school	%	NHSC	4.39	16.448	37.25	6.449
Education: high school	%	HISC	7.03	24.788	37.67	5.189
Education: associate	%	ASSO	16.8	28.513	38.659	4.489
Education: bachelor	%	BACH	7.52	18.518	34.75	5.507
Education: graduate	%	GRAD	4.47	11.742	37.04	5.087
Average number of years of education	#	EDUC	11.04	13.15	16.06	0.85
Cars per household in 2012*	Veh/HH	CARH	1.171	1.682	2.094	0.121
0 available car in household	%	CAR1	1.3	6.512	28.4	5.278
1 available car in household	%	CAR2	15.4	29.671	42.7	6.042
2 available cars in household	%	CAR3	21.5	40.218	50.4	5.015
3 available cars in household	%	CAR4	5.2	15.960	24.4	4.096
4 available cars in household	%	CAR5	1.4	5.516	13.5	2.341
>4 available cars in household	%	CAR6	0.3	2.122	11.1	1.449

* 2012 data is used in some cases which is the closest estimation for the 2010 data.

Variables, data collection process and the source of data are described as follows:

- Age: this is an ordinal variable with 6 categories (i.e., <20, 20-24, 25-34, 35-44, 45-64, and >65) to represent the percentage share of each age group in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information. The average age in the UA is also another studied variable.

- Race: this is a nominal variable with 6 categories (i.e., Hispanic, White, Asian, Black, Indian, and Others) to represent the percentage share of each race group in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information.
- Non-locals: this variable represents the percentage of the population who are born outside the UA. City Data online website [98] is the source for this information.
- Gender: this is a binary variable (1 represents male and 0 comes for female) to represent the percentage of each gender of residents in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information. The ratio of male percentage to the female percentage is also calculated.
- Language: this is a nominal variable with 5 categories (i.e., English, Spanish, Asian, Indo/European, and Others) to represent the percentage share of each language group in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information. The percentage of non-English speakers (100-ENGL) is also calculated.
- Household size: this is a nominal variable with 3 categories (i.e., small family, medium family, and large family) to represent the percentage share of each family size group in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information. The average household size is another studied variable.
- Marital status: this is a nominal variable with 5 categories (i.e., married, never

married, divorced, widowed, and separated) to represent the percentage share of each marital status in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information. The percentage of non-married population (100-MARR) is also calculated.

- Owner occupied and renter occupied: these two percentage variables represent the property status in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information.
- Annual household income: this is an ordinal variable with 5 categories (i.e., <$25K, $25K-$49K, $50K-$75K, $75K-$150K, and >$150k) to represent the percentage share of each income group in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information.
- Employment: this is a nominal variable with 3 categories (i.e., employed, unemployed, and armed forces) to represent the percentage share of each employment type in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information.
- Education: this is an ordinal variable with 5 categories (i.e., no high school, high school, associate, bachelor, and graduate) to represent the percentage share of each education group in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information. EDUC represents the average number of education yeas in a UA, calculated from other education variables.
- Car ownership: this is an ordinal variable with 6 categories (i.e., 0 available car, 1 available car, 2 available cars, 3 available cars, 4 available cars, and >4 available cars) to represent the percentage share of each car ownership group in the UA. City

Data online website [98] and Find the Home online website [99] are the sources for this information. The average number of cars per average number of household in the UA (i.e., cars per household) in 2012 is also included.

3.3.4. Transportation Network Characteristics

Table 3.5 contains a list of transportation network characteristics as well as their descriptions, units and descriptive statistics. This part of the database is mostly assembled data for year 2010. However, the closest available time period is used for some variables (as reported in the table), when the 2010 data is not available.

TABLE 3.5: Transportation network related variables, descriptions, units and statistics

Variable and Description	**Unit**	**Acronym**	**Min**	**Mean**	**Max**	**St. D.**
Share of transportation mode: car	%	CARR	39.9	82.789	93.95	11.074
Share of transportation mode: bike	%	BIKE	0.05	1.323	12.38	1.947
Share of transportation mode: public	%	PUBL	0.50	6.339	38.69	7.380
Share of transportation mode: taxi	%	TAXI	0.47	1.374	6.43	0.858
Share of transportation mode: walk	%	WALK	0.84	4.196	15.16	3.104
Share of transportation mode: work at home	%	HOME	1.84	3.979	11.68	1.550
Walking score	#	WSCOR	18	89	48.29	15.861
Pavement condition: poor	%	PVCP	0.01	0.260	0.64	0.147
Pavement condition: mediocre	%	PVCM	0.09	0.273	0.48	0.085
Pavement condition: fair	%	PVCF	0.05	0.153	0.32	0.055
Pavement condition: good	%	PVCG	0.05	0.313	0.71	0.160
Weighted average of pavement condition variables (-3*PVCP)+(-1*PVCM)+(1*PVCF)+(3*PVCG)	%	INDEX	-1.98	0.038	1.99	0.93
Travel Time Index (TTI: congestion intensity)	Ratio	TTIR	1.04	1.171	1.37	0.067
Percent of congested lane miles (congestion extent)	%	COEX	9	39.4	80	14.49
Length of peak hour periods (congestion duration)	Hrs	CODU	1.5	3.453	8	1.443
Congestion costs per auto commuter	$	COCO	125	548.11	1568	284.9
Percent of trucks on freeways in 2008*	%	HEVE	3.446	7.943	17.449	2.478
Percent of commuters in single occupant vehicles in 2012**	%	SOVP	48.963	77.852	87.230	6.423
Network miles per square mile	NetworkMile/SqMile	NMSM	4.586	11.0	43.447	4.042
Freeway miles per square mile	FwyMile/SqMile	FMSM	0.081	0.320	1.667	0.171
Freeway lane miles per 1K commuters	FwyLM/K-Commut.	FLMC	0.254	1.357	2.995	0.493
Freeway and arterial miles per capita	(Fwy+Art)Mile/pop	FAMC	0	0.001	0.002	0
Network links per network nodes	Links/Nodes	NLNN	1.111	1.267	1.453	0.056
Nodes per network mile in upper-level system	Nodes/NetworkMile	NONM	4.530	7.245	10.326	1.153
Nodes per square mile	Nodes/SqMile	NOSM	5.17	14.55	66.88	7.33
Freeway lane miles per total network lane miles	FwyLM/NetworkLM	FLMN	0.024	0.074	0.167	0.024
Gini coefficient of population per network mileage	Ratio	GIPO	0.204	0.349	0.995	0.157
Gini coefficient of workers per upper-level network mileage	Ratio	GIWO	0.546	0.823	0.993	0.105
Transit vehicle revenue miles per square mile	TransitVRM/SqMile	TVSM	2350.9	42813	278438	45381
Transit vehicle revenue miles per capita	TransitVRM/Pop	TVPC	1.49	13.43	49.04	8.45
Average commuting travel time in minutes in 2012**	Minutes	CTIM	17.6	23.897	35.2	3.622
Commuting travel time <10 min	%	TIM1	5.3	12.126	28.61	3.855
Commuting travel time: 10-19 min	%	TIM2	18.3	36.318	50.8	6.921
Commuting travel time: 20-29 min	%	TIM3	13.04	23.987	30.9	3.504
Commuting travel time: 30-44 min	%	TIM4	6.6	17.388	30.8	5.657
Commuting travel time: 45-60 min	%	TIM5	1.4	4.714	13.7	2.449
Commuting travel time >60 min	%	TIM6	1.92	5.462	25.73	3.468
Work departure time: before 6 AM	%	WDT1	3.705	10.788	25.359	3.649
Work departure time: 6-8 AM	%	WDT2	30.240	42.908	52.490	4.145
Work departure time: 8-10 AM	%	WDT3	16.0	25.523	44.60	5.265
Work departure time: 10-12 AM	%	WDT4	3.319	4.923	7.875	0.801
Work departure time: noon-midnight	%	WDT5	9.141	15.855	23.88	3.072

* 2008 data is used in some cases which is the closest estimation for the 2010 data.
** 2012 data is used in some cases which is the closest estimation for the 2010 data.

Variables, data collection process and the source of data are described as follows:

- Share of transportation modes: this is a nominal variable with 6 categories (i.e., car, bike, public, taxi, walk, work at home) to represent the percentage share of each transportation mode in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information.
- Walking score [108]: walking score is an index to measure walkability. Walk scores of 0-24 and 25-49 represent car dependent situations where almost all errands require a car and most errands require a car, respectively. Walk score of 50-69 represents a somewhat walkable situation where some errands can be accomplished on foot. Walk score of 70-89 is considered as a very walkable situation where most errands can be accomplished on foot. Finally, walk score of 90-100 represents a walker's paradise where daily errands do not require a car [109].
- Pavement condition: this is an ordinal variable with 4 categories (i.e., poor, mediocre, fair, good) to represent the percentage share of each pavement condition group in the UA. Long-term Pavement Performance (LTPP) [110] is the source for this information. The weighted average of pavement condition variables ($(-3 \times PVCP) + (-1 \times PVCM) + (1 \times PVCF) + (3 \times PVCG)$) is another studied variable.
- Congestion intensity: Travel Time Index (TTI) is a measure to represent congestion intensity and is found in the UMR, published by the Texas Transportation Institute [54, 97]. TTI measures congestion intensity based on how much longer it takes to drive on a road in congested conditions compared to free-flow condition.
- Congestion extent: this variable represents the portion of lane-miles that are

congested and is found in the UMR, published by the Texas Transportation Institute [54, 97].

- Congestion duration: this variable represents the length of peak periods and is found in the UMR, published by the Texas Transportation Institute [54, 97]. The peak periods are derived from the calculated hourly TTIs.
- Congestion costs: this variable represents the average traffic congestion cost per each auto commuter in 2010 in the UA.
- Presence of heavy vehicles: this variable represents the percent of trucks on freeways, published by FHWA's [107] Highway Statistics series.
- Single Occupant Vehicles (SOVs): this variable represents the percent of commuters in SOVs, published by FHWA's [107] Highway Statistics series.
- Network miles per square mile: this variable represents the network density by the ratio of network miles per square mile. To calculate this variable, total UA network mileage, from the FHWA [107], is divided by UA square mileage from the 2010 Census data [7, 54].
- Freeway miles per square mile: this variable represents network density by the ratio of freeway miles per square mile. To calculate this variable, total UA freeway mileage, from the FHWA [107], is divided by UA square mileage from the 2010 Census data [7, 54].
- Freeway lane miles per 1,000 commuters: this variable represents network density by the ratio of freeway lane-miles per 10,000 commuters. To calculate this variable, total UA freeway lane-mile, from the UMR [97], is divided by UA number of commuters from the 2010 UMR data [54, 97].

- Freeway and arterial miles per capita: this variable represents network density by the ratio of freeway and arterial miles per capita. To calculate this variable, total UA freeway and arterial miles, from the FHWA [107], is divided by UA population from the 2010 UMR data [54, 97].
- Network links per network nodes: this variable represents the network connectivity by the ratio of number of links per number of nodes in the UA network. To calculate this variable, the 2010 census tracts [7] and TransCAD street layer [101] are first used to find all the streets inside the UA network and then number of links and nodes [54]. It is worth mentioning that a link is basically a road segment while a node is a point that traffic flow is interrupted (e.g., intersection, on-ramp, off-ramp and stop sign).
- Nodes per network mile in upper-level system: this variable represents the network connectivity by the ratio of number of nodes per network mile in the UA network. To calculate this variable, the 2010 census tracts [7] and TransCAD street layer [101] are first used to find all the upper-level network roadways inside the UA network and then number of nodes [54]. Nodes per square mile is also another studied variable, derived from this variable.
- Freeway lane-miles per total network lane-miles: 2010 UMR and FHWA data are used to calculate the freeway lane-miles and total network lane-miles [54, 97, and 107].
- Gini coefficient of population per network mileage: this variable is a ratio to represent the variation in population per network mileage within the UA [54]. To calculate the Gini coefficient of population per network mileage for the UA, first

the population in each census tract, from the Census data [7], is divided by the network mileage from the TransCAD street layer [101]. These ratios are then compared across all census tracts of the UA to show the variation of population per network mileage within the UA [54].

- Gini coefficient of workers per upper-level network mileage: this variable is a ratio used to represent the variation in the number of workers per upper-level (freeways, expressways and major arterials and connectors) network mileage within the UA [54]. To calculate the Gini coefficient of workers per upper-level network mileage for the UA, first the number of workers in each census tract, from the Census data [7], is divided by the upper-level network mileage from the TransCAD street layer [101]. These ratios are then compared across all census tracts of the UA to show the variation of population per network mileage within the UA [54].
- Transit vehicle revenue miles per square mile: vehicle revenue miles for all types of transit, from the National Transit Database [111], is divided by UA square mileage from the Census data [7, 54]. Transit vehicle revenue miles per capita is also another studied variable.
- Commuting travel time: this is an ordinal variable with 6 categories (i.e., <10 min, 10-19 min, 20-29 min, 30-44 min, 45-60 min, and >60 min) to represent the percentage share of each travel time group in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information. The average commuting travel time in the UA in 2012 is also included.
- Work departure time: this is an ordinal variable with 5 categories (i.e., Before 6 AM, 6-8 AM, 8-10 AM, 10-12 AM, and Noon-Midnight) to represent the

percentage share of each departure time group in the UA. City Data online website [98] and Find the Home online website [99] are the sources for this information.

CHAPTER 4: METHODOLOGY

4.1. Introduction

The Structural Equation Modeling (SEM) technique is used in this research to model the complex relationships between several different urban characteristics and traffic safety. Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) tools are first used to study the possible interrelationships among a set of independent variables by constructing a factor representing the covariance structure of these variables. EFA, CFA and SEM are briefly described in this section. Let us define some common terms before explaining EFA and CFA:

- Observed variables: variables that are directly collected or measured. They are also called indicator or manifest variables [112].
- Latent variables: variables which are not directly observed or measured and are formed from observed ones. A generated factor in factor analysis is considered a latent variable [112].
- Path Analysis (PA): the direct and indirect relationships between variables is a path analysis, similar to multiple regression analysis [112].
- Exogenous variables: variables that are not influenced by other variables in the model structure are called exogenous (independent) variables [112].
- Endogenous variables: variables that are influenced by other variables in the model structure are called endogenous (dependent) variables [112].

4.2. Explanatory Factor Analysis (EFA)

EFA is a statistical technique used to identify the underlying factor structure of a set of observed variables. It can be used when there is no a priori hypothesis about the patterns of observed variables that form the factors (latent variables). In fact, EFA is used when the knowledge of theory (coming from the literature or practical results) are not clear enough to hypothesize the relationships among a set of variables that may construct and be representative of a common concept (common factor). It is described as an orderly simplification of interrelated measures without imposing a preconceived structure on the outcome [113].

EFA extracts common factors to capture as much common variance as possible in the first factor. Subsequent factors account for the maximum amount of the remaining common variance until no common variance remains [113]. Maximum likelihood method is used to estimate the factor loadings in this research. Factor loadings measure the effect of a common factor on the measured variables. These loadings are actually the coefficients of a linear regression between the observed variable and the generated latent variable (factor) [114].

Variables are assumed to be metric (or dummy) and the minimum sample size should be at least 5 times the number of observed variables in a factor analysis. Also, a linear correlation between observed variables (i.e., some level of collinearity but not an extreme degree) above 30 percent is required before the EFA. Unlike many other statistical techniques, multivariate normality is not required in EFA (however the statistical inference will improve with normality) [115].

EFA and PCA (Principal Component Analysis) are two major data reduction techniques, however there are several differences between them. The components of PCA are actual orthogonal linear combinations that maximize the total variance, while in EFA, the factors are linear combinations that maximize the shared portion of the variance. PCA is generally used when the goal is to reduce the correlated observed variables to a smaller set of important independent composite variables, however in factor analysis, a theoretical model of latent factors can be generated or verified [116].

4.3. Confirmatory Factor Analysis (CFA)

EFA is first used to detect the potential patterns among the observed variables. Then the knowledge of theory is used to construct the pattern among other interrelated measures. Finally, these constructed structures (from the EFA) and hypothesized structures (from the theoretical and conceptual relationships) are tested and verified statistically using CFA. In fact, CFA statistical technique serves to verify the factor structure of a set of observed variables and is used to test the existence of a hypothesized relationship between observed variables and their underlying latent constructs [113]. In other words, CFA is used to test how well the measured variables represent the number of constructs. The main difference between EFA and CFA is that in EFA all measured variables are related to every latent variable while it is possible in CFA to specify the number of factors and which measured variable is related to which latent variable. This capability makes CFA a powerful tool to confirm or reject the measurement theory. The major assumptions of CFA are multivariate normality, minimum sample size, and random sample for the dataset [117].

4.4. Structural Equation Modeling (SEM)

The next step after the factor analysis is to construct the structural equation model (SEM). SEM models the complex relationship among multiple dependent and independent variables through a combination of statistical methods and assumptions. The SEM approach is the most advanced tool available to address various endogeneity issues as well as multilevel cause-effect relationships, as it allows for complex interdependencies among variables. SEM allows for estimation of the two-way relationships among dependent variables. It is also widely used as it avoids the disadvantages of estimating each variable in a separate regression model and having large number of regressions. Also, this method allows for constructing relationships among both observed and unobserved (latent) variables, as well as interdependencies among the endogenous variables. Thus, it enables researchers to test hypotheses even when experiments are not possible and there is no observed data (or the observed data does not represent the whole population). There are several conceptual terms and parameters used and addressed in SEM technique, as follows:

- CFA is used to verify and test whether a hypothesized relationship structured between observed and latent variables is consistent [112].
- Hybrid is a combination of PA and CFA [112].
- Each variable in an SEM framework can act both as a dependent and an independent variable, simultaneously [112, 118].
- Direct effects: the direct effect of one variable on another variable [119].
- Indirect effects: the total effect of all indirect relationships from one variable to another variable, "which consist of all paths from one variable to another variable, mediated by at least one additional variable. There are some techniques to estimate the indirect effects that are transmitted by the selected variables rather than by all variables" [119].
- Measurement model for the independent variables (exogenous variables): this

model accounts for the contribution of each latent independent variable to observed variables (Figure 4.1) [112, 118].

- Measurement model for the dependent variables (endogenous variables): this model accounts for the contribution of each latent dependent variable to observed variables (Figure 4.1) [112, 118].
- Structural model between latent endogenous and exogenous variables: this model constructs and measures the hypothesized relationship between latent variables (Figure 4.1) [112, 118].
- Covariance structure model: "since the SEM implies a structure for the covariance between the observed variables, some sources use covariance structure model for this technique" [120].

Combination of both measurement and structural models, including every exogenous and endogenous observed or latent variable, shown in Figure 4.1, forms the integrated SEM structure. In fact, PA, CFA and PA are used in an SEM structure [112].

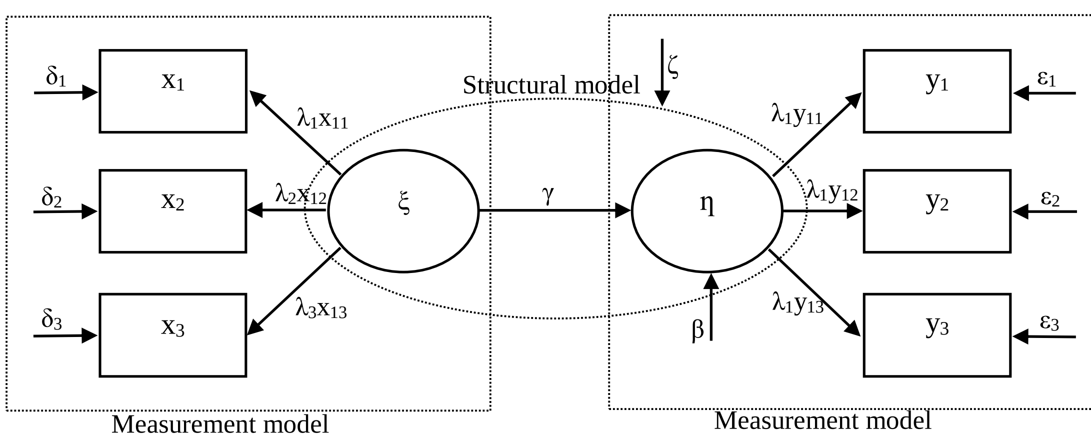

FIGURE 4.1: SEM structure [112].

The SEM regresses the effect of exogenous (i.e., independent) variables on endogenous (i.e., dependent) variables through structural components. The effects among endogenous variables (i.e., collinearity) are also modeled in the measurement component. The measurement and structural models can be expressed as Equations 4.1 and 4.2, respectively [112, 118]:

$$\begin{bmatrix} y \\ x \end{bmatrix} = \begin{bmatrix} \theta_y & 0 \\ 0 & \theta_x \end{bmatrix} \begin{bmatrix} \eta \\ \xi \end{bmatrix} + \begin{bmatrix} \varepsilon \\ \delta \end{bmatrix} \tag{4.1}$$

$$\eta = \beta\eta + \Gamma\xi + \zeta \tag{4.2}$$

where:

x: $(q \times 1)$ column vector of observed exogenous variables

y: $(p \times 1)$ column vector of observed endogenous variables

ξ: $(n \times 1)$ column vector of latent exogenous variables

η: $(m \times 1)$ column vector of latent endogenous variables

δ: $(q \times 1)$ column vector of measurement error terms for observed variables x

ε: $(p \times 1)$ column vector of measurement error terms for observed variables y

θ_x: the matrix $(q \times n)$ of structural coefficients for latent exogenous variables to their observed indicator variables

θ_y: the matrix $(p \times m)$ of structural coefficients for latent endogenous variables to their observed indicator variables

Γ: the matrix $(m \times n)$ of regression effects for exogenous latent variables to endogenous latent variables

β: the coefficient matrix $(m \times m)$ of direct effects between endogenous latent variables

ζ: $(m \times 1)$ column vector of error terms

Coefficients of an SEM model are estimated by covariance analysis where the differences between observations and predictions are minimized iteratively [112, 118].

CHAPTER 5: URBAN FORM AND TRAFFIC SAFETY

5.1. Introduction

This chapter focuses on the relationship between urban form characteristics and traffic safety. Both overall traffic safety and pedestrian safety are studied and modeled separately. First, urban form latent factors are generated using factor analysis techniques (CFA and EFA). Then, path analysis (SEM structure) is developed to test the hypothesized direct and indirect relationships between dependent safety variables and generated urban form factors.

5.2. Factor Analysis – Urban Form and Traffic Safety

As explained before, EFA is first used to identify the interrelationships among observed variables, especially when there is no hypothesized relationship based on the knowledge of theory. Then, CFA is used to confirm the structures generated by EFA and on the basis of other hypothesized structures. The final latent factors are then determined from significant attributes for use in further analysis.

It is worth mentioning that the most common way to conduct a CFA is to develop the structure of hypothesized latent common factors using the related observed variables and check the significance level of associated coefficients. Thus, multiple different combinations of interrelationships among various attributes of urban form are controlled using the AMOS tool in SPSS software as well as Stata software to find the most significant structure to construct meaningful and significant latent factors. Several hypothesized structures as well as the outputs of EFA are controlled at this stage. The specification resulting from this trial-and-error model selection process is then used to set up the structure of the SEM.

Figure 5.1 shows the final structures of factors found to be meaningful and statistically significant in measuring the independent latent variables in our modeling framework. Values in the figures represent standardized coefficients of observed variables significant mostly at 5% (and 10% in a few cases) that construct latent variables. Statistical significance levels (p-value) under 0.01 and under 0.05 are shown by **, and *, respectively. Over 87% of observed variables have standardized coefficients over 0.40.

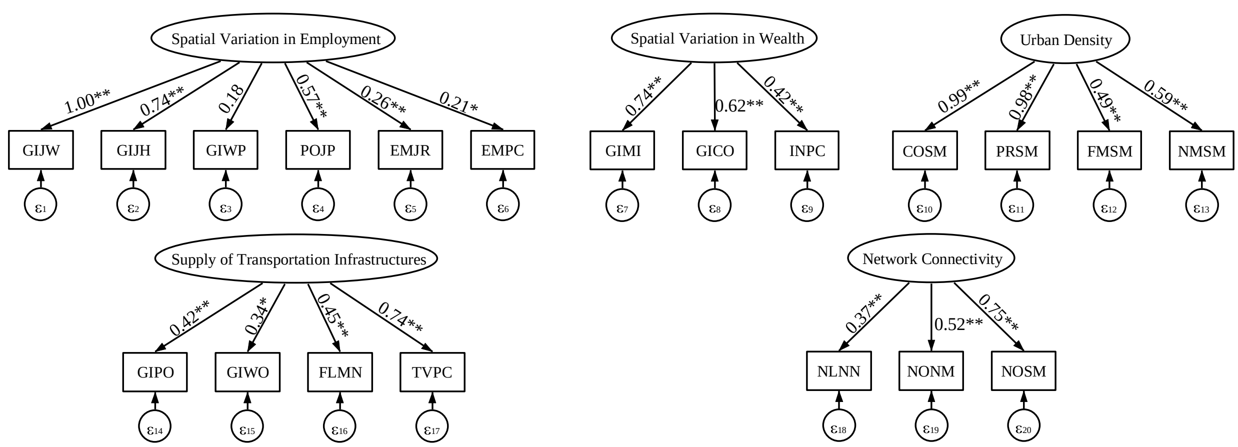

FIGURE 5.1: Urban form factors - independent latent variables.

Five latent factors (Figure 5.1) are generated to represent the independent variables of urban form in this study:

- Spatial variation in employment: this latent factor is formed from six observed variables (i.e., Gini coefficient of jobs per worker, Gini coefficient of jobs per household, Gini coefficient of workers per population, percent of population in job-poor tracts, percent of employment in job-rich and job-dense tracts, and employment per capita). This factor represents one of the most important characteristics of urban form, namely the housing-employment balance. The higher the spatial variation in employment value, the more uneven the distribution of job attractive centers in a UA and also the more unbalanced the distribution of employment versus housing. This variable can also be used as a proxy of monocentricity and polycentricity. The lower the value of this factor, the higher the polycentricity index of a UA.

- Spatial variation in wealth: this latent factor is formed from three observed variables (i.e., Gini coefficient of household median income, Gini coefficient of car ownership per household, and income per capita). This factor represents the spatial distribution of different social classes across the UA. The higher the spatial variation in wealth, the more uneven the distribution of social classes in a UA.
- Urban density: this latent factor is formed from four observed variables (i.e., number of commuters per square mile, number of residents per square mile, freeway miles per square mile, and transport network miles per square mile). This factor represents the development density of a UA. The higher the urban density value, the more the development density (including residents, employments and road networks) in a UA.
- Supply of transportation infrastructures: this latent factor is an independent variable, formed from four observed variables (i.e., Gini coefficient of population per upper-level transport network mileage, Gini coefficient of workers per upper-level transport network mileage, the ratio of freeway lane-miles per total network lane-miles, and transit vehicle revenue miles per capita). This factor represents one

of the most important characteristics of urban form, the supply of upper-level transport network (e.g., highways and freeways) and public transit in a UA. The higher the supply of transportation infrastructures value, the more the high-level transportation infrastructures supply for residents and commuters.

- Network connectivity: this latent factor is formed from three observed variables (i.e., network links per network nodes, nodes per network mile in upper-level system, and number of nodes per square mile). This factor represents the connectivity of the UA's transportation network, which is also an infrastructure characteristic of urban form. The higher the network connectivity value, the more the connection between transportation infrastructures in a UA. This variable can also be used as a proxy of accessibility. The higher the value of this factor, the higher the level of accessibility.

Figures 5.2 shows the final latent structure for two latent mediators that represent some features specific to the transportation network:

- Traffic congestion: this latent factor is a mediator variable, formed from four observed variables (i.e., TTI (travel time index: the congestion intensity), percent of congested lane-miles, length of peak-hour periods, and congestion cost per commuter). The higher the traffic congestion value, the more the congested roadways in a UA.
- Non-driving transportation modes: this latent factor is another mediator variable, formed from three observed variables (i.e., share of public transportation, share of biking, and share of walking). This factor represents the use of green transportation in a UA. The higher the non-driving transportation modes value, the higher the use

of green transportation modes in a UA.

FIGURE 5.2: Latent mediators.

Figure 5.3 shows the structure of the only dependent latent factor, traffic safety. This latent factor is formed from five observed variables (i.e., number of fatal crashes per 100,000 population, number of fatalities per 100,000 population, number of persons involved in fatal crashes per 100,000 population, number of vehicles involved in fatal crashes per 100,000 population, and fatal crashes involving drunken person per 100,000 population). The higher the traffic safety value, the more the incidence of fatal crashes and the lower the traffic safety in the UA. In fact, this latent factor shows the incidence rate of fatal traffic crashes however it is called traffic safety here. Thus, it is necessary to pay attention as to how we can correctly interpret this factor in upcoming models represented in this research. Four of the five standardized coefficients are well over 0.90, while the fifth one is shy of 80%.

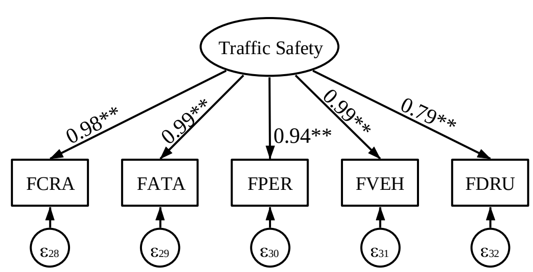

FIGURE 5.3: Traffic safety factor – latent dependent variable.

5.3. Path Analysis: SEM – Urban Form and Traffic Safety

The hypothesized SEM structure is modeled at this stage, including connections between all independent variables (urban form factors) and the dependent variable (traffic safety factor). Indirect effects (i.e., the connection through a mediator) are modeled as well as direct effects. Then, insignificant variables are iteratively removed from the hypothesized structure in a backward selection process. The significant relationships are finally kept in the model, after several iterations. It is worth restating that the connections (relationships) between variables are assumed to be linear in the SEM structure.

Figure 5.4 represents the final estimated SEM model. Independent latent factors of urban form, latent factors of transportation network features as mediators, control variables (some demographic and geographic characteristics) and the dependent latent factor of traffic safety are the four different categories of variables in this figure. Numerical values represent standardized coefficients of variables significant mostly at 5% (and 10% in a few cases) that construct the final PA. The statistical significance levels (p-value) under 0.01, and under 0.05 are shown by ** and *, respectively.

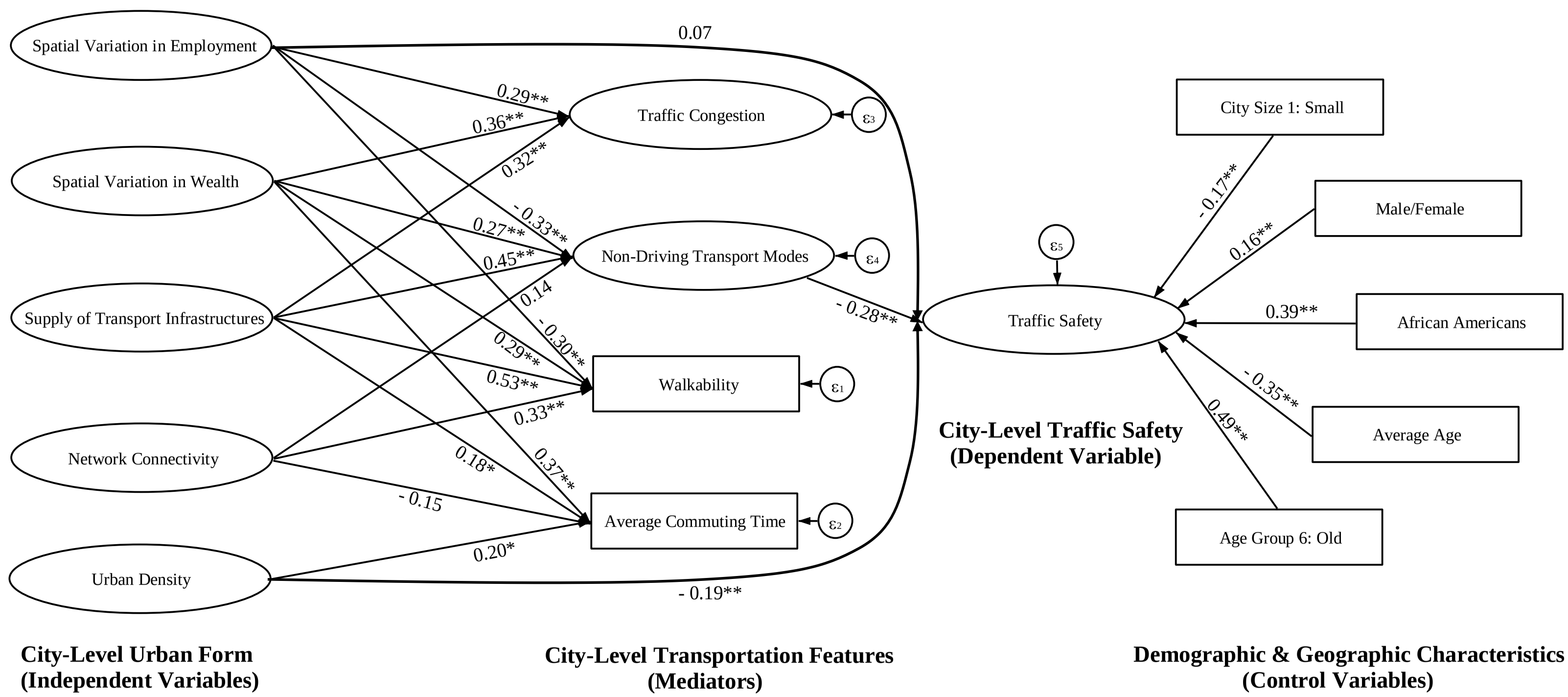

FIGURE 5.4: Estimated SEM model – urban form and traffic safety.

*Ovals represent latent factors and rectangles represent observed variables

The PA (Figure 5.4) contains three types of relationships: 1) the structural part which forms the relationships between significant independent latent factors and the dependent variable, 2) the indirect effect of independent latent factors on the dependent variable through some significant mediators, and 3) the relationship between significant control variables and the dependent variable.

Also, the sensitivity analysis of the estimated SEM model to determine the relative magnitude of effects on traffic safety is represented in Table 5.1. For this purpose, all observed variables forming a specified latent factor are simultaneously increased by 10% while other observed variables are constant at their mean value. In this way, the magnitude of the specified latent factor will increase by 10% of its expected mean. This value is then multiplied by the unstandardized coefficient of the latent factor to calculate the sensitivity for a direct effect (in the case of indirect effect, the value will be multiplied by the coefficient of the latent factor and the coefficient of the mediator). The resulting value is the expected change in the value of the traffic safety latent factor after 10% change in the specified latent factor. Next, the expected change in each observed variable forming the traffic safety latent factor is calculated using this value. The final stage involves transforming these values to a percentage change in the observed variables forming the traffic safety latent factor.

It is worth mentioning that Table 5.1 only represents a summary of the calculated results which is the effect of a 10% simultaneous change in all observed variables forming each latent factor, while other latent variables are kept constant, on the main observed variable of traffic safety latent factor, FCRA: the rate of fatal crashes per 100,000 populations in 2010. Indeed, other observed variables of traffic safety (FATA, FPER, FVEH, FDRU) can be directly obtained using the weighting loads of the represented traffic safety latent structure. Thus, FCRA is the only one we report and interpret here. However, a more complete table, including coefficients and values for all 5 observed variables of traffic safety factor, is represented in the Appendix A.1.

TABLE 5.1: Sensitivity analysis – urban form and traffic safety

Independent Variable (Latent)	Change in Observed Independent Variables (%)		Effect Type	Associated Change in Observed FCRA Dependent Variable (%)
	Variable	Change		
Spatial Variation in Employment	GIJW	- 10	Direct	- 3.26
	GIJH	- 10		
	GIWP	- 10		
	POJP	- 10		
	EMJR	- 10		
	EMPC	- 10		
Spatial Variation in Employment	GIJW	- 10	Indirect	- 2.63
	GIJH	- 10		
	GIWP	- 10		
	POJP	- 10		
	EMJR	- 10		
	EMPC	- 10		
Urban Density	COSM	+ 10	Direct	- 2.04
	PRSM	+ 10		
	FMSM	+ 10		
	NMSM	+ 10		
Spatial Variation in Wealth	GIMI	+ 10	Indirect	- 2.28
	GICO	+ 10		
	INPC	+ 10		
Supply of Transportation Infrastructures	GIPO	+ 10	Indirect	- 2.02
	GIWO	+ 10		
	FLMN	+ 10		
	TVPC	+ 10		
Network Connectivity	NLNN	+ 10	Indirect	- 1.73
	NONM	+ 10		
	NOSM	+ 10		

In relation to the objectives of this research, the main results derived from the model can be summarized as follows:

- Only two of the hypothesized independent factors of urban form are found to have a direct effect on traffic safety, namely spatial variation in employment and urban density.
- Indirect effects of urban form on traffic safety are all through a single mediator, namely non-driving transport modes. Interestingly, the effects of congestion, walkability, and average commuting time are not statistically significant.

- Spatial variation in employment has a significant direct effect on traffic safety. Uneven spatial distribution of employment decreases traffic safety. A 10% decrease in the variables associated with spatial variation of employment (i.e., 10% simultaneous decrease in Gini coefficients of jobs per worker, jobs per household and workers per population, ratio of population in job-poor areas and ratio of employment in job-rich areas) will decrease the rate of fatal crashes by 3.26%. In fact, strongly monocentric UAs could potentially increase the risk of traffic fatalities compared to more polycentric UAs.
- Greater spatial variation in employment not only directly increases the risk of traffic fatalities, but also has an indirect negative effect on traffic safety. Uneven spatial distribution in job-housing balance decreases the use of green transportation modes, which consequently results in a decrease in traffic safety. A 10% reduction in spatial variation of employment can decrease the rate of fatal crashes in a UA by 2.63%, indirectly through its effect on the use of green transport modes. In fact, the total effect of a 10% increase in polycentricity can be a reduction of 5.89% (3.26%+2.63%) in fatal crashes. Obviously, the magnitude of the direct effect is higher compared to the indirect effect.
- Urban density has a statistically significant direct effect on traffic safety. Denser UAs are less prone to traffic fatalities. It is estimated that a simultaneous 10% increase in COSM (commuters per square mile), PRSM (residents per square mile), FMSM and NMSM (freeway miles and network miles per square mile) can decrease the rate of fatal crashes by 2.04%.
- The use of non-driving modes of transportation (biking, public transit and walking)

has a large effect on traffic safety and reduces the incidence of traffic fatalities. However, this factor is considered as a mediator in this research to account for the indirect effect of urban form characteristics on traffic safety.

- Spatial variation in wealth has an indirect effect on traffic safety through its effect on the use of non-driving transport modes. A more even spatial distribution of different social classes among different tracts of a UA increases the use of driving, resulting in an increase in traffic fatalities. A 10% more even distribution of wealth in society increases the risk of traffic fatal crashes by 2.28%.
- Supply of upper-level transport facilities and infrastructures increases traffic safety indirectly. The larger supply of infrastructures (especially transit facilities, since TVPC is the most effective variable to form this latent factor) will increase the share of green transportation, and consequently it decreases the risk of fatal crashes. A 10% increase in public transit supply and high-level freeways can reduce fatalities by 2.02%.
- Network connectivity is another urban form factor that indirectly increases traffic safety. The higher the network connectivity, the higher the share of non-driving transport modes, and thus the lower the risk of traffic fatalities. A 10% increase in network connectivity can increase traffic safety by 1.73%.
- The risk of fatal crashes in small UAs is lower than in other UAs.
- In UAs with a higher ratio of males and African-Americans, the risk of fatal crashes increases.
- While in general terms, average age increases traffic safety, older users (more than 65 years) are the most dangerous users of the transportation network, in terms of

traffic safety.

5.4. Path Analysis: SEM – Urban Form and Pedestrian Safety

Independent and mediator latent factors tested in the previous section for their overall traffic safety are also used to model the effect of urban form characteristics on pedestrian safety. The hypothesized structure of this model is the same as for overall traffic safety, except for replacing the overall traffic safety (the latent variable formed from other five traffic safety attributes, FCRA, FATA, FPER, FVEH, and FDRU) by the pedestrian safety (the observed variable of FPED: pedestrian fatalities).

Figure 5.5 represents the final estimated SEM model for pedestrian safety. Independent latent factors of urban form, latent factors of transportation network features as mediators, observed control variables (some demographic and geographic characteristics) and observed pedestrian fatalities dependent variable are the four different categories of variables in this figure. Numerical values represent standardized coefficients of variables significant mostly at 5% (and 10% for a few cases) that construct the final PA. The statistical significance levels (p-value) under 0.01, and under 0.05 are shown by ** and *, respectively.

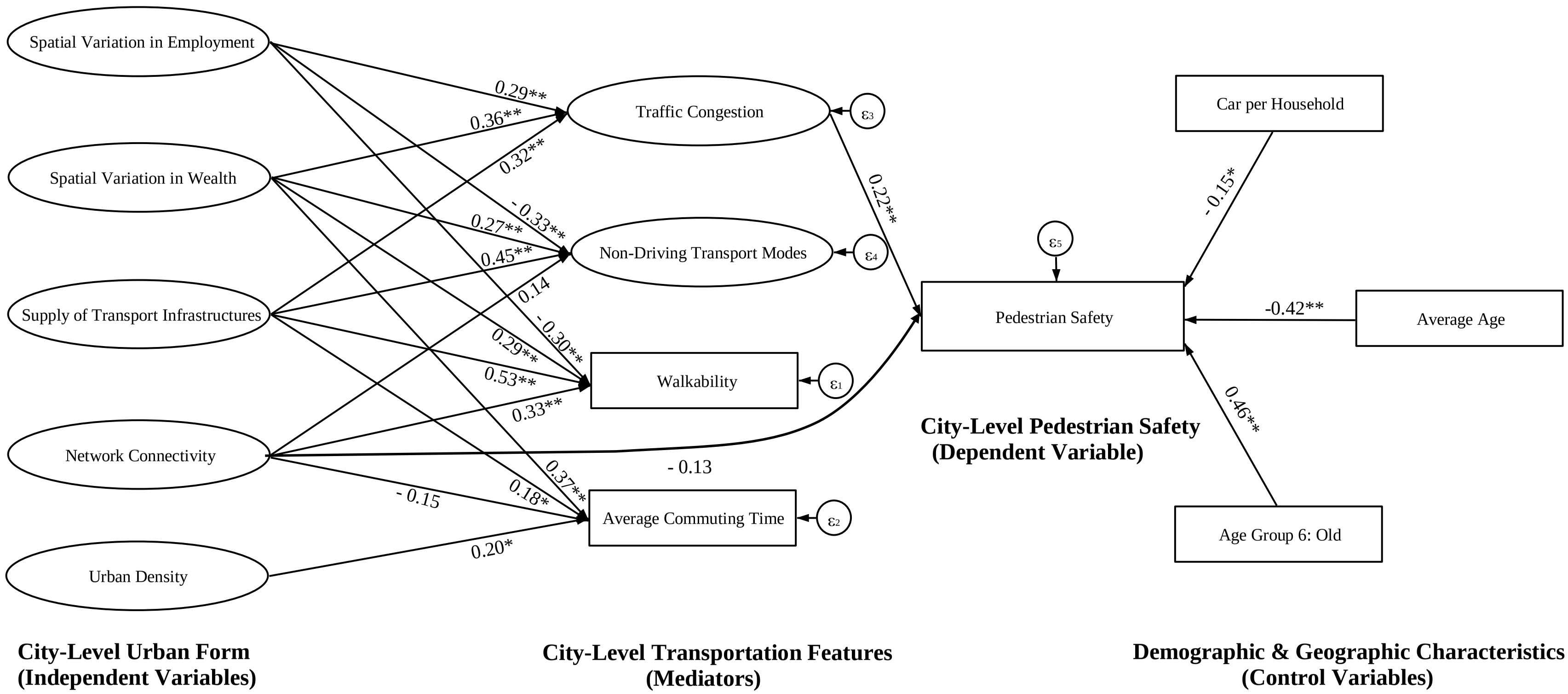

FIGURE 5.5: Estimated SEM model – urban form and pedestrian safety.

Table 5.2 represents the sensitivity analysis of the estimated SEM model, conducted according the same principles are earlier. The effect of a 10% simultaneous change in observed variables forming each latent factor, while other latent variables are kept constant, on pedestrian safety is reported in this table. A more complete version of this table is represented in Appendix A.2.

TABLE 5.2: Sensitivity analysis – urban form and pedestrian safety

Independent Variable (Latent)	**Change in Observed Independent Variables (%)**		**Effect Type**	**Associated Change in Observed FPED Dependent Variable (%)**
	Variable	**Change**		
Spatial Variation in Employment	GIJW	- 10	Indirect	- 5.48
	GIJH	- 10		
	GIWP	- 10		
	POJP	- 10		
	EMJR	- 10		
	EMPC	- 10		
Spatial Variation in Wealth	GIMI	- 10	Indirect	- 7.12
	GICO	- 10		
	INPC	- 10		
Supply of Transportation Infrastructures	GIPO	- 10	Indirect	- 3.92
	GIWO	- 10		
	FLMN	- 10		
	TVPC	- 10		
Network Connectivity	NLNN	+ 10	Direct	- 17.85
	NONM	+ 10		
	NOSM	+ 10		

In relation to the objectives of this research, the main results derived from the model can be summarized as follows:

- Network connectivity is the only hypothesized independent variable of urban form found to have a direct effect on pedestrian traffic safety.
- All indirect effects of urban form on pedestrian traffic safety are through a single mediator, namely traffic congestion. Interestingly, the effects of non-driving transport modes, walkability, and average commuting time fail to be significant.
- Urban density has no effect on the traffic safety of pedestrians.
- Network connectivity is the most important urban form factor affecting pedestrian safety. This effect is exclusively direct. The higher the network connectivity, the

lower the incidence rate of pedestrian fatalities. A 10% increase in network connectivity can increase pedestrian safety by 17.85%.

- Traffic congestion is a significant factor that mediates the effect of urban form factors on pedestrian safety. The higher the traffic congestion on roadways, the greater the incidence of pedestrian fatalities.
- Spatial variation in employment has a significant indirect effect on pedestrian safety through traffic congestion. Uneven spatial distribution of employment and job-housing balance increases traffic congestion on the road network and consequently decreases pedestrian safety. A 10% decrease in the variables associated with spatial variation of employment (i.e., 10% decrease in Gini coefficients of jobs per worker, jobs per household and workers per population, ratio of population in job-poor areas and ratio of employment in job-rich areas) will decrease the rate of pedestrian fatalities by 5.48%, indirectly. In fact, more monocentric UAs could potentially increase the risk of pedestrian fatalities in contrast to a more polycentric structure of the UA.
- Spatial variation in wealth has an indirect effect on pedestrian traffic safety through its effect on traffic congestion. A more even spatial distribution of different social classes among different tracts of a UA decreases the traffic congestion, resulting in an increase in pedestrian safety. A 10% increase in even distribution of wealth among different tracks will increase pedestrian safety by 7.12%.
- Supply of upper-level transportation facilities and infrastructures decreases pedestrian safety indirectly. The larger supply of infrastructures translates into increased traffic congestion, and consequently increases the risk of pedestrian

crashes. A 10% increase in high-level transportation supply can raise pedestrian fatality rates by 3.92%.

- Although generally average age, increases pedestrian safety, a greater share of older people (more than 65 years) is found to compromise pedestrian safety.
- Car ownership is a significant control variable in the model. Higher number of passenger cars per household is associated with a lower risk of pedestrian fatality.

5.5. Conclusions

This chapter focuses on the relationship between urban form and traffic safety. For this purpose, urban form is measured by five macro-level latent factors, including a) spatial variation in employment which measures housing-employment balance and can be used as a proxy for monocentricity, b) urban density which measures the development density, c) spatial variation in wealth which measures the uneven spatial distribution of different social classes in a UA, d) supply of transportation infrastructures which measures the level of residents' accessibility to public transit and upper-level transport networks, and e) network connectivity which measures the level of connection between transportation infrastructures and can be considered as a proxy for accessibility.

The traffic congestion latent factor, share of non-driving transportation modes latent factor, walkability and average commuting time were transportation features hypothesized to mediate the effect of urban form on traffic safety and pedestrian safety.

The overall traffic safety is measured by traffic safety latent factor, formed from five observed variables and pedestrian safety is measured by the ratio of pedestrian fatalities. Two separate SEM models were developed to study the overall traffic safety and pedestrian safety.

The main difference between the overall traffic safety model and the pedestrian safety model is their mediator variable. The use of non-driving transportation modes mediates urban form factors in the first model and traffic congestion mediates urban form factors in the second model. In fact, encouraging the use of green transportation modes would be an effective policy to increase overall traffic safety in UAs, while controlling traffic congestion would be effective to decrease pedestrian crashes.

Job-housing balance affects both overall traffic safety and pedestrian safety. More balanced and even job-housing spatial distribution in UAs, increases the use of non-driving transportation modes and decreases traffic congestion. Thus, more polycentricity increases traffic and pedestrian safety.

Urban density has a direct effect on traffic safety, but not on pedestrian safety. Denser UAs are generally safer.

The effect of spatial distribution of wealth on the use of non-driving transportation modes and consequently on overall traffic safety seems to require further research to be covered in next chapters. However, the even spatial distribution of different social classes amongst different tracts of a UA effectively reduces traffic congestion and consequently increases pedestrian safety indirectly.

The supply of high-level transportation infrastructures including public transit, freeways and highways has a two-sided effect on overall traffic safety and pedestrian safety. More supply of transportation infrastructure increases overall traffic safety while decreasing pedestrian safety indirectly.

Connectivity in a transportation network increases the share of non-driving transport modes and consequently increases the overall traffic safety indirectly. This factor also increases the pedestrian safety directly.

In summary, urban form features have noteworthy effects on the overall traffic safety and pedestrian safety in UAs. Increasing the share of non-driving transportation modes and reducing traffic congestion will help to reduce traffic crashes and pedestrian crashes, respectively. In addition, urban density, job-housing balance and network connectivity are the most effective urban form factors for traffic safety planners to consider. In this regard, providing more public transit, controlling traffic congestion, planning for polycentric urban designs with a more even distribution of jobs and housing (mixed land-uses), increasing urban development density (decreasing sprawl), increasing network connectivity and accessibility are suggested are smart land-use planning to create safer urban environment for drivers and pedestrian.

CHAPTER 6: TRIP GENERATION AND TRAFFIC SAFETY

6.1. Introduction

This chapter focuses on the relationship between trip generation and traffic safety. Both overall traffic safety and pedestrian safety are studied and modeled separately. First, trip generation indicators, including both trip generation latent factors and observed variables, are introduced. For this purpose, EFA and CFA are used to form latent factors of trip generation. Then, path analysis (SEM structure) is developed to test the hypothesized direct and indirect relationships between dependent safety variables and observed and latent trip generator variables.

6.2. Factor Analysis – Trip Generation

As explained earlier, EFA and CFA are used to find the interrelationships among observed variables and form significant latent factors. Figure 6.1 shows the results of this iterative process, which consist in factors of trip generation to be used as independent latent variables. Statistical significance levels (p-value) under 0.01 and under 0.05 are shown by **, and * in this figure, respectively.

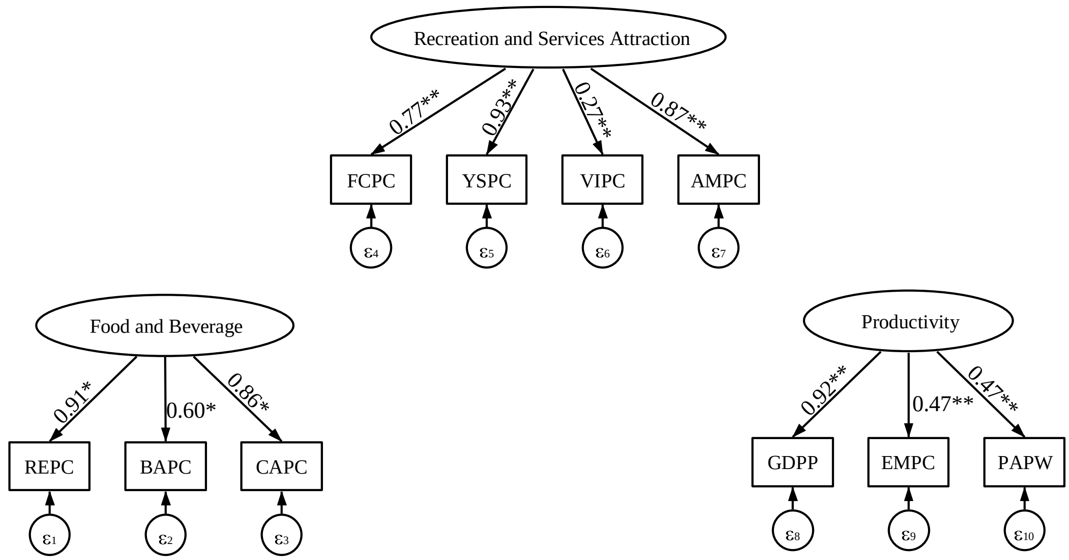

FIGURE 6.1: Trip generation factors - independent latent variables.

Three latent factors are generated to represent independent variables of macro-level trip generation in this study:

- Recreation and services attraction: this latent factor is formed from four observed variables (i.e., fitness centers per capita, yoga studios per capita, vice per capita, and number of alternate medicine centers per capita). This factor represents one of the most important trip attraction characteristics. The higher the value of recreation and services attraction factor, the more the trip generation in a UA and consequently the more the need for transportation.
- Food and beverage: this latent factor is formed from three observed variables (i.e., number of restaurants per capita, number of bars per household, and number of cafes per capita). This factor represents the density of food and beverage attraction centers in the UA. The higher the value of food and beverage factor, the more the need for local transport and consequently the higher the trip generation.
- Productivity: this latent factor is formed from three observed variables (i.e., GDP

per capita, employment per capita, and number of patents per number of workers). This factor represents the level of economic development and productivity in a society. The higher the productivity value, the more the economic growth in the society and consequently the more the need for transportation.

It is worth mentioning that some other observed indicators of macro-level trip generation are studied in this chapter along with some latent factors, including presence of heavy vehicles on the road network, in-commuting flow per workers, long-term change in population, day- and night-time population density, average household size, rate of unemployment, income per capita, number of religious organizations per capita and average level of education. These attributes do not form any significant latent factor and are going to be considered as observed independent variables in the modeling process.

Other latent factors studied in this chapter were presented in the previous chapter (Figures 5.2 and 5.3): two latent mediators of traffic congestion and non-driving transportation modes, and a single dependent latent factor of traffic safety.

6.3. Path Analysis: SEM – Trip Generation and Traffic Safety

The hypothesized SEM structure is modeled at this stage, including connections between all independent variables and the dependent variable. Indirect effects (i.e., the connection through a mediator) are modeled as well as direct effects. Hypothesized independent variables are directly or indirectly related to trip production/attraction and are regarded as some individual macro-level trip generation indicators, including a) urban features that are related to trip generation (e.g., percentage change in population, day- and night-time population density), b) observed trip generation characteristics (e.g., in-commuting flow per worker, number of religious organizations per capita, number of professional sport teams per capita, total number of grocery stores per capita), c) developed latent factors of trip generation (e.g., productivity, food and beverage, and recreation and services attraction), d) transportation network features that are related to trip generation (e.g., presence of heavy vehicles) and e) household characteristics that are related to trip generation (e.g., income per capita, average number of years of education, unemployment rate, average household size, median housing cost per median household income).

A number of control variables are hypothesized in this model, namely city size, geographic region, annual precipitation, average monthly rent, ratio of retail employees over government employees, percentage of married and non-married residents, ratio of males over the females, percentage of non-English speakers, percentage of different races (e.g., Black, White, Hispanic), average age, and percentage of different age cohorts (e.g., over 65 years old and less than 20 years old).

The hypothesized mediators include some transportation features, namely observed average commuting time, observed walking score, latent traffic congestion and latent share of non-driving modes, which mirrors the approach used in the previous models in chapter 5. The latent factor of traffic safety (introduced in chapter 5) is considered as the only dependent variable in this model. As explained earlier, the hypothesized model consists of all possible direct and indirect relationships between the mentioned variables. Nonsignificant variables are iteratively removed from the hypothesized structure in a step-by-step backward selection process. The significant relationships are kept in the final estimated SEM model, represented in Figure 6.2. Numerical values represent standardized coefficients of variables significant at 5% that construct the final PA. Statistical significance levels (p-value) under 0.01, and under 0.05 are noted by ** and *, respectively.

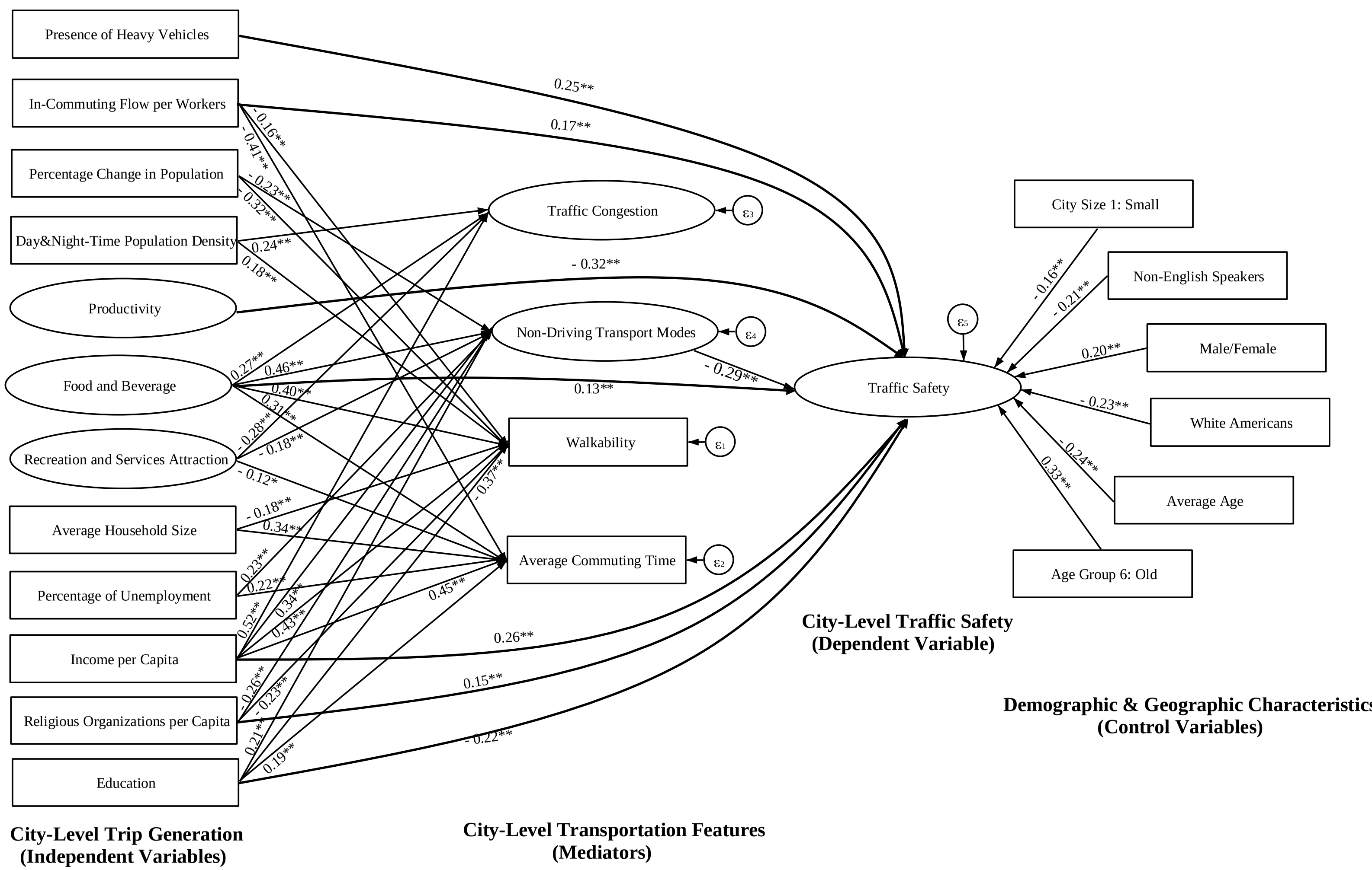

FIGURE 6.2: Estimated SEM model – trip generation and traffic safety.

Sensitivity analysis of the estimated SEM model is conducted following the same approach as in Chapter 5 and results are reported in Table 6.1. The effect of a 10% change in independent variables (either observed independent variables or observed variables that form each latent factor) on traffic safety, while other variables are kept constant, is reported in this table. A more complete version of this table is presented in the Appendix A.3.

TABLE 6.1: Sensitivity analysis – trip generation and traffic safety

Independent Variable (Latent/Observed)	**Change in Observed Independent Variables (%)**		**Effect Type**	**Associated Change in Observed FCRA Dependent Variable (%)**
	Variable	**Change**		
Presence of Heavy Vehicles	HEVE	- 10	Direct	- 4.63
In-Commuting Flow per Workers	COFW	- 10	Direct	- 0.60
Percentage Change in Population	POPP	- 10	Indirect	- 0.52
Productivity	GDPP	+ 10	Direct	- 5.99
	EMPC	+ 10		
	PAPW	+ 10		
Food and Beverage	REPC	- 10	Direct	- 2.74
	BAPC	- 10		
	CAPC	- 10		
Food and Beverage	REPC	+ 10	Indirect	- 2.80
	BAPC	+ 10		
	CAPC	+ 10		
Recreation and Services Attraction	FCPC	- 10	Indirect	- 0.37
	YSPC	- 10		
	VIPC	- 10		
	AMPC	- 10		
Percentage of Unemployment	UEMP	+ 10	Indirect	- 1.44
Income per Capita	INPC	- 10	Direct	- 3.81
Income per Capita	INPC	+ 10	Indirect	- 4.51
Religious Organizations per Capita	ROPC	- 10	Direct	- 2.27
Religious Organizations per Capita	ROPC	- 10	Indirect	- 1.13
Education	EDUC	+ 10	Direct	- 19.60
Education	EDUC	+ 10	Indirect	- 5.41

In relation to the objectives of this research, the main results derived from the model can be summarized as follows:

- As in the model of urban form effects, indirect effects of trip generation on traffic safety are all through a single moderating variable, namely non-driving transport modes. Also, the effects of congestion, walkability, and average commuting time are not statistically significant.
- Day-time and night-time population density and average household size have no

statistically significant effect (whether direct or indirect) on traffic safety.

- Presence of heavy vehicles has a significant direct effect on traffic safety. A 10% decrease in the ratio of heavy vehicles on the road network can directly reduce the rate of fatal crashes by 4.6%.
- In-commuting flow has a direct effect on crash rate. A 10% reduction in the ratio of workers who commute into the UA for work can reduce traffic fatalities by 0.6%.
- Long-term change in population density decreases the use of non-driving transport modes and indirectly increases the incidence of traffic fatalities. This effect is weak however: 0.52% reduction in fatalities for a 10% drop in population.
- Productivity has a significant direct effect on traffic safety. A 10% increase in productivity (i.e., 10% increase in GDP per capita, employment rate and number of patents) will increase traffic safety by 6%. In fact, economic development and growth in quality of life could potentially increase traffic safety in a UA.
- Density of certain urban traffic generators such as food and beverage establishments has both direct and indirect effects on the rate of fatal traffic crashes. A 10% increase in food and beverage attraction will increase traffic fatalities by 2.7%. On the other hand, increase in food and beverage attraction will increase the use of green transportation and consequently reduces traffic fatalities by 2.8% indirectly. Thus, these two-sided effects of food and beverage attraction on traffic safety cancel each other overall.
- Increase in recreation and services attraction will slightly increase the risk of traffic crashes indirectly.
- A 10% increase in unemployment rate is associated with a 1.4% reduction in traffic

fatalities.

- Income per capita has also a two-sided effect on traffic safety. Higher income per capita is associated with more trip generation and consequently more crashes. On the other hand, it is effective to increase the share of green transport modes and accordingly decrease the incidence of traffic crashes. In total, the effect of income per capita on traffic safety could be minimal.
- Religious organizations are one of the most important trip generation centers in a UA. The higher the number of religious organizations per capita in a UA, the higher the incidence of traffic crashes. A 10% increase in the number of religious organizations is associated with a 3.4% increase in traffic fatalities, both directly (by increasing trip generation) and indirectly (through decreasing the use of non-driving modes).
- Education is one of the most effective macro-level attributes to increase traffic safety. A 10% increase in the average number of years of education for the residents of a UA is associated with a 19.6% positive direct and 5.4% positive indirect effect (through increasing the use of green transportation) on traffic safety.
- The risk of fatal crashes in small UAs is generally lower than in other UAs.
- In UAs with a higher ratio of males and non-White Americans, the rate of fatal crashes increases.
- While in general, average age of the population increases traffic safety, the transportation network is found to be more dangerous when elderlies (over 65) are a larger share of the population.

6.4. Path Analysis: SEM – Trip Generation and Pedestrian Safety

The same set of hypothesized observed and latent independent variables and mediators tested in the model of overall traffic safety is also used to model the effect of macro-level trip generation characteristics on pedestrian safety. The hypothesized structure of this model is also the same, except that pedestrian safety (the observed variable of FPED: pedestrian fatalities) replaces the latent variable formed from the other five traffic safety attributes (FCRA, FATA, FPER, FVEH, and FDRU).

Figure 6.3 represents the final estimated SEM model for pedestrian safety. Independent observed and latent trip generation features, observed and latent transportation network features that are treated as mediators, control variables (some demographic and geographic characteristics) and pedestrian fatalities dependent observed variable form the four different categories of variables in this model. Numerical values represent standardized coefficients of variables significant at 5% that construct the final PA. The statistical significance levels (p-value) under 0.01, and under 0.05 are shown by ** and *, respectively.

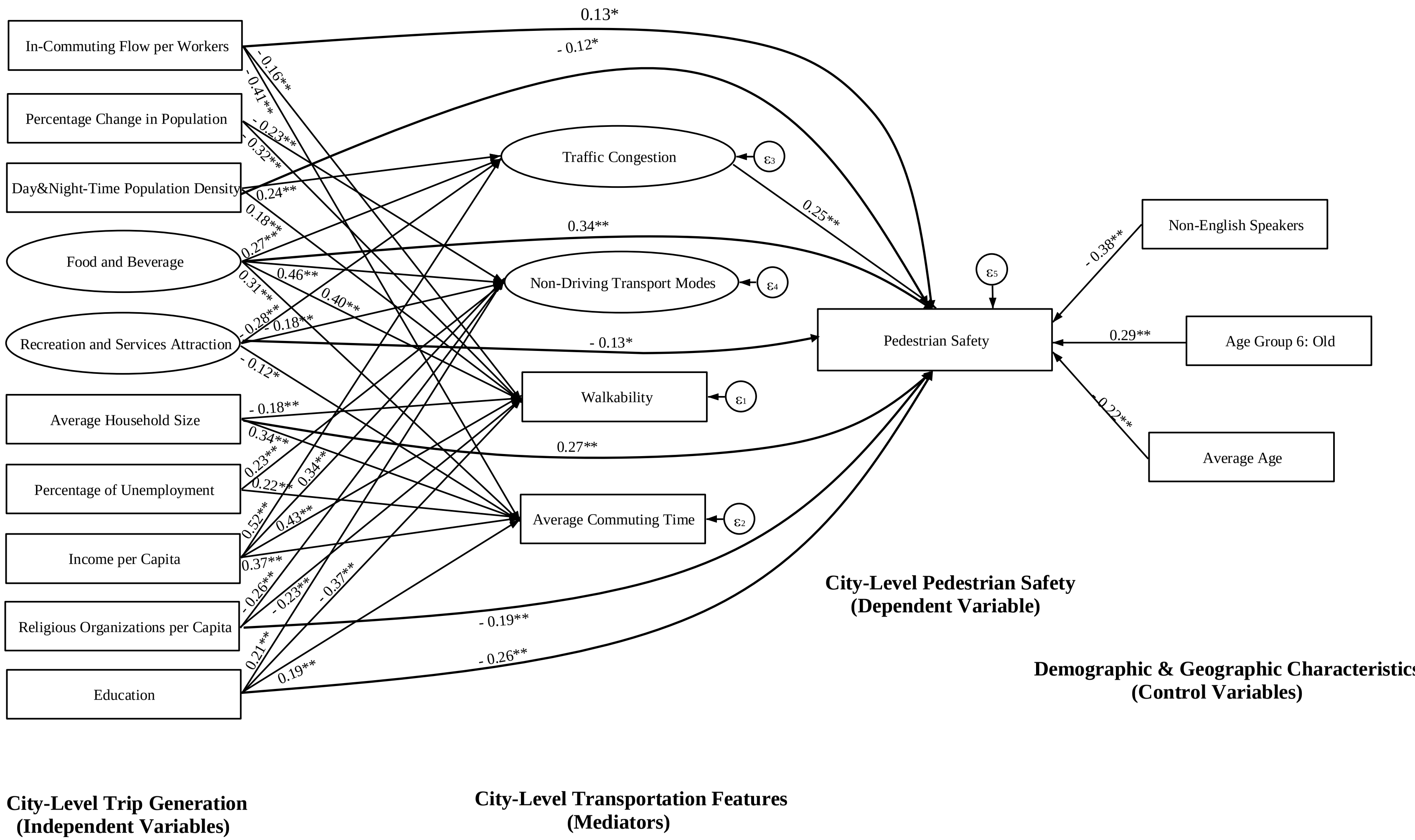

FIGURE 6.3: Estimated SEM model – trip generation and pedestrian safety.

Table 6.2 reports on the sensitivity analysis of the estimated SEM model. The effect of 10% change in observed variables and latent factors (simultaneous change in observed variables forming each latent factor) on pedestrian safety, while other variables are kept constant, is reported in this table. A more complete version of this table is represented in the Appendix A.4.

TABLE 6.2: Sensitivity analysis – trip generation and pedestrian safety

Independent Variable (Latent/Observed)	Change in Observed Independent Variables (%)		Effect Type	Associated Change in Observed FPED Dependent Variable (%)
	Variable	Change		
In-Commuting Flow per Workers	COFW	- 10	Direct	- 1.24
Day & Night-Time Population Density	COPRSM	- 10	Direct	- 1.71
Day & Night-Time Population Density	COPRSM	- 10	Indirect	- 2.85
Food and Beverage	REPC	- 10	Direct	- 19.69
	BAPC	- 10		
	CAPC	- 10		
Food and Beverage	REPC	- 10	Indirect	- 3.49
	BAPC	- 10		
	CAPC	- 10		
Recreation and Services Attraction	FCPC	+ 10	Direct	- 2.58
	YSPC	+ 10		
	VIPC	+ 10		
	AMPC	+ 10		
Recreation and Services Attraction	FCPC	+ 10	Indirect	- 1.37
	YSPC	+ 10		
	VIPC	+ 10		
	AMPC	+ 10		
Average Household Size	AHHS	- 10	Direct	- 31.37
Income per Capita	INPC	- 10	Indirect	- 1.79
Religious Organizations per Capita	ROPC	+ 10	Direct	- 7.89
Education	EDUC	+ 10	Direct	- 65.32

In relation to the objectives of this research, the main results derived from the model can be summarized as follows:

- The effects of city-level trip generation variables on pedestrian traffic safety tend to be direct.
- All indirect effects of trip generation on pedestrian traffic safety are through a single moderating variable, namely traffic congestion. Interestingly, the effects of non-driving transport modes, walkability, and average commuting time fail to be

significant.

- In-commuting flow has a significant direct effect on pedestrian safety. A 10% reduction in the ratio of workers who commute into the UA for work can reduce pedestrian fatalities by 1.2%.
- Day- and night-time population density (i.e., sum of night-time residents' density and day-time commuters' density) increases the incidence of pedestrian crashes both directly (by 1.7%) and indirectly (by 2.8%).
- The density of urban attraction centers (food and beverage establishments) has both direct and indirect effects on the rate of fatal pedestrian crashes. A 10% increase in food and beverage attraction will increase pedestrian fatalities by 19.7% directly, as an important cause of pedestrian oriented trips in a UA. In addition, increase in food and beverage attraction will increase the traffic congestion and consequently increases pedestrian fatalities by 3.5% indirectly. Thus the combined direct and indirect effects are estimated to be 23.2%.
- Increases in recreation and services attraction will decrease the incidence of pedestrian crashes by 4%, both directly and indirectly. Providing more services in each neighborhood will effectively reduce the need for walking to access such services.
- Greater average household size is significantly associated with an increase in pedestrian fatalities. The higher number of people in a household, the lower the chance of using the household's passenger car for commuting and consequently the higher the probability of walking.
- Income per capita also has indirect significant effect on pedestrian safety. Higher

income will require higher level of activity (higher traffic congestion) and potentially higher risk of pedestrian crashes.

- Although religious organizations were important trip generation elements to increase the incidence of traffic crashes in general, they reduce the risk of pedestrian crashes in specific terms. A 10% increase in the number of religious organizations is associated with a 7.9% decrease in pedestrian fatalities.
- Education is one of the most effective macro-level attributes not only to increase overall traffic safety, but also to increase pedestrian safety. A 10% increase in the average number of years of education for the residents of a UA is associated with a 65% positive direct effect on pedestrian safety.
- UAs with a higher ratio of non-English speakers have fewer fatal pedestrian crashes, maybe because this type of residents contribute less in the UA's economic development.
- While in general, average age increases pedestrian safety, old residents (more than 65) raise the risk in terms of pedestrian safety.

6.5. Conclusions

This chapter focused on the relationship between trip generation and traffic safety at the city level. For this purpose, trip generation is measured by three macro-level latent factors, including a) recreation and services attraction which is a proxy for daily travel demand, b) food and beverage as a proxy for leisure activities trips, and c) productivity as a proxy of economic development and quality of life, and some other observed variables, such as long-term percentage change in population, day-time and night-time population density, in-commuting flow per worker, number of religious organizations per capita, number of professional sport teams per capita, total number of grocery stores per capita, presence of heavy vehicles, income per capita, average number of years of education, unemployment rate, average household size, and median housing cost per median household income.

Traffic congestion latent factor, share of non-driving transportation modes latent factor, walkability and average commuting time were transportation features hypothesized to mediate the effect of urban form on traffic safety and pedestrian safety.

The overall traffic safety is measured by traffic safety latent factor, formed from five observed variables and pedestrian safety is measured by the rate of pedestrian fatalities. Two separate SEM models were developed to study the overall traffic safety and pedestrian safety, respectively.

As for the effect of urban form, the main difference between the overall traffic safety model and the pedestrian safety model is their mediator variable. The use of non-driving transportation modes mediates urban form factors in the first model and traffic congestion mediates urban form factors in the second model. In fact, encouraging the use of green transportation modes would be an effective policy to increase overall traffic safety in UAs, while controlling traffic congestion would be effective to decrease pedestrian crashes.

Presence of heavy vehicles on the road network, as a specific component of trip generation, directly increases the risk of traffic fatalities, but not pedestrian fatalities. In-commuting flow of workers into the UA also increases the risk of traffic and pedestrian crashes directly.

Day-time and night-time population density (residential and employment density) has a significant effect on pedestrian safety. Higher population density is associated with the higher risk of pedestrian crashes. However, this factor does not affect overall traffic safety.

The density of food and beverage attractions has a significant effect on pedestrian safety, but not on traffic safety. A higher density of food attractions is associated with an increase in pedestrian flow and also traffic congestion, and consequently increases the risk of pedestrian crashes.

Providing more recreation and services for residents decreases the need for transportation (either by non-driving modes or driving modes) and consequently reduces the traffic congestion as well as the share of green transportation. Thus, providing more local recreation and services centers slightly increases in traffic crashes but effectively decreases pedestrian crashes.

Religious organizations are important trip generators and have significant two-sided effects on traffic safety. The higher the number of religious organizations in a UA, the higher the rate of traffic fatalities and the lower the rate of pedestrian fatalities. Long-distance travel to non-local areas to access religious organizations might explain this two-sided effect.

Household size and income per capita are two effective household characteristics (and trip generators) that influence traffic safety. UAs with higher household size are more prone to pedestrian crashes (limited number of personal passenger cars will force the large families to have more pedestrian-based trips). UAs with higher income per capita are expected to have more economic activities, higher congestion and consequently higher pedestrian crashes.

The level of education, as an important human-related factor, increases both traffic and pedestrian safety. Increase in EDUC means an increase in the average number of year of education for the residents of a UA. Indeed, this attribute is a high-level and long-term policy variable, however this requires further research in the field of transportation policy making to elucidate the causal role of this variable in lowering the risk of a fatal crash.

In summary, trip generation features have noteworthy effects on the overall traffic safety and pedestrian safety in UAs. In general, increasing the share of non-driving transportation modes and reducing traffic congestion will help to reduce traffic crashes and pedestrian crashes, respectively. Mixed land-use designs (providing access to local religious organizations, food and beverage centers, recreation and services for residents) followed by pedestrian safety standards are highly recommended. Thus, residents in mixed land-use and pedestrian-oriented communities do not require long-distance trips for daily demands. Controlling the in-commuting flow of workers from sub-urban areas into the UA by setting a different work schedule helps to reduce traffic congestion and the risk of traffic crashes. In addition, regulating the transportation of heavy vehicles (e.g., limiting heavy vehicles' transportation in day-time) can increase traffic safety. Finally, providing more accessible public transportation for UAs with large average household size helps to enhance pedestrian safety.

CHAPTER 7: INTEGRATED MODEL FOR TRAFFIC SAFETY IN URBAN AREAS

7.1. Introduction

This chapter studies the joint effect of all macro-level urban characteristics on traffic safety, including urban form factors, trip generation attributes and transportation network features. Indeed, this chapter combines two previous models (urban form & traffic safety and trip generation & traffic safety) and considers all the hypothesized independent variables together. The main objective of this chapter is to identify the most effective parameters, out of all the studied city-level attributes, to enhance traffic safety and pedestrian safety in UAs. One can argue that the two previous models were comprehensive enough to study traffic safety and pedestrian safety. However, it is vital for policy makers to prioritize the effective factors and evaluate their relative importance and ranking, while considering macro-level factors all together. The other reason to develop an integrated model would be the existing interrelationships between independent variables (urban form, trip generation and transportation network). Urban form and trip generation attributes not only affect traffic safety, but also affect each other as well. Thus, this integrated analysis enables a closer identification of likely causal relationships.

In this chapter, overall traffic safety and pedestrian safety are modeled separately. All introduced latent factors and observed variables of urban form and trip generation are considered at this stage. Path analysis (SEM structure) is developed to test the hypothesized direct and indirect relationships between dependent safety variables and observed and latent trip generators, urban form factors and transportation network features.

7.2. Path Analysis: SEM – Integrated Model for Traffic Safety

The hypothesized SEM structure is modeled at this stage, including connections between all independent variables and the dependent variable. Indirect effects (i.e., the connection through a mediator) is modeled as well as direct effects. Macro-level hypothesized independent variables contain: a) generated urban form latent factors (i.e., spatial variation in employment, spatial variation in wealth, urban density, supply of transportation infrastructures and network connectivity), b) other city-level urban characteristics (e.g., percentage change in population, day- and night-time population density), c) generated trip generation latent factors (e.g., productivity, food and beverage, and recreation and services attraction), d) observed trip generators (e.g., in-commuting flow per worker, number of religious organizations per capita, number of professional sport teams per capita, total number of grocery stores per capita), e) transportation network features (e.g., presence of heavy vehicles, supply of public transit, the ratio of single occupant vehicles on the road network, pavement condition index), and f) household characteristics (e.g., income per capita, average number of years of education, unemployment rate, average household size, median housing cost per median household income). These independent variables cover a broad range of macro-level components of a city as a complex socio-physical system.

A number of control variables are hypothesized in this model, namely car ownership, city size, geographic region, annual precipitation, type of energy uses, average monthly rent, ratio of retail employees over government employees, percentage of married and non-married residents, ratio of males over the females, percentage of non-English speakers, percentage of different races (e.g., Black, White, Hispanic), average age, and percentage of different age categories (e.g., over 65 years old and less than 20 years old) are hypothesized control variables in the model. The hypothesized mediators are transportation features, including observed average commuting time, observed walking score, latent traffic congestion and latent share of non-driving modes. Finally, traffic safety latent factor is considered as the single dependent variable in this model.

The hypothesized model consists of all possible direct and indirect relationships between the above-mentioned variables. Non-significant variables are iteratively removed from the hypothesized structure in a step-by-step backward selection process. The significant relationships are kept in the final estimated SEM model, represented in Figure 7.1. Numerical values represent standardized coefficients of variables significant at 5% that construct the final PA. The statistical significance levels (p-value) under 0.01, and under 0.05 are shown by ** and *, respectively.

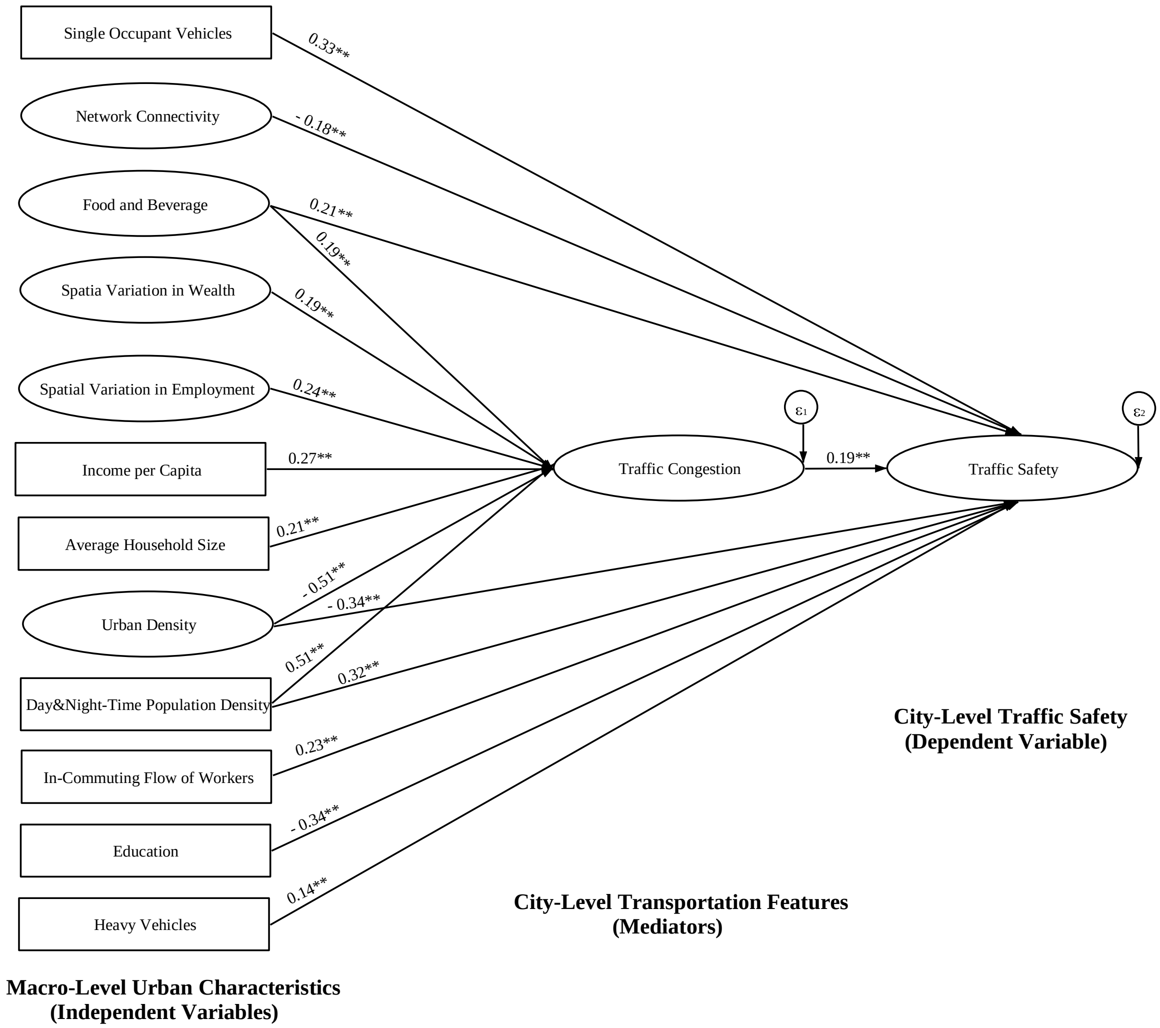

FIGURE 7.1: Integrated SEM model for traffic safety.

The sensitivity analysis of the integrated SEM model to determine the relative magnitude of effects on traffic safety is represented in Table 7.1, following the same approach as in Chapters 5 and 6. The effect of a 10% change in each independent variable (either independent observed variable or all observed variables that form each latent factor), while other variables are kept constant, on the main observed variable of traffic safety latent factor (FCRA) is reported in this table. A more complete version of this table is presented in the Appendix A.5.

TABLE 7.1: Sensitivity analysis – macro-level urban characteristics and traffic safety

Independent Variable (Latent/Observed)	Change in Observed Independent Variables (%)		Effect Type	Associated Change in Observed FCRA Dependent Variable (%)
	Variable	**Change**		
Single Occupancy Vehicles	SOVP	- 10	Direct	- 27.41
Network Connectivity	NLNN	+ 10	Direct	-13.75
	NONM	+ 10		
	NOSM	+ 10		
Food and Beverage	REPC	- 10	Direct	- 5.18
	BAPC	- 10		
	CAPC	- 10		
Food and Beverage	REPC	- 10	Indirect	- 0.89
	BAPC	- 10		
	CAPC	- 10		
Spatial Variation in Wealth	GIMI	- 10	Indirect	- 1.87
	GICO	- 10		
	INPC	- 10		
Spatial Variation in Employment	GIJW	- 10	Indirect	- 2.27
	GIJH	- 10		
	GIWP	- 10		
	POJP	- 10		
	EMJR	- 10		
	EMPC	- 10		
Income per Capita	INPC	- 10	Indirect	- 4.60
Average Household Size	AHHS	- 10	Indirect	- 1.95
Urban Density	COSM	+ 10	Direct	-4.08
	PRSM	+ 10		
	FMSM	+ 10		
	NMSM	+ 10		
Urban Density	COSM	+ 10	Indirect	- 1.23
	PRSM	+ 10		
	FMSM	+ 10		
	NMSM	+ 10		
Day & Night-Time Population Density	COPRSM	- 10	Direct	- 6.05
Day & Night-Time Population Density	COPRSM	- 10	Indirect	- 7.30
In-Commuting Flow per Workers	COFW	- 10	Direct	- 0.94
Education	EDUC	+ 10	Direct	-35.76
Presence of Heavy Vehicles	HEVE	- 10	Direct	- 3.01

In relation to the objectives of this research, the main results derived from the model can be summarized as follows:

- Unlike the urban form and trip generation models (in chapters 5 and 6), the mediator in the integrated model is traffic congestion instead of non-driving transportation modes. This can be explained by the compound effect of multiple significant independent variables, especially because the SOVs variable (with a negative strong correlation with the use of non-driving transportation modes) is significant in the model. The mediation effects of green transportation modes, walkability, and average commuting time are not statistically significant.

- Some statistically significant variables in the urban form and trip generation models have lost their significance in the integrated model, such as productivity, recreation and services attraction, and religious organizations attraction. This can be explained by existence of multicollinearity between studied independent variables in the integrated model.
- The ratio of single occupant vehicles on the road networks has a significant direct and negative effect on the risk of fatal crashes. A 10% increase in the rate of SOVs is associated with a 27.4% increase in the rate of traffic fatalities.
- Network connectivity increases traffic safety directly. A 10% increase in the transportation network connectivity can directly reduce the rate of traffic crashes by 13.7%. The estimated effect of this factor on traffic safety in the urban form model (chapter 5) was 1.7%, indirectly through increasing the use of green transportation modes. Different types of effect (direct vs indirect) can be a reason for this difference in the magnitude of the effects (13.7% vs 1.7%).
- Food and beverage attraction has both direct and indirect effects on traffic safety. A 10% increase in the density of food and beverage attractions can increase the risk of fatal traffic crashes by 6.07% in total (5.18% directly + 0.89% indirectly). However, the compound reported effect of this factor in the trip generation model (chapter 6) was almost minimal.
- Spatial variation in wealth has an indirect effect on traffic safety, same as in the urban form model (chapter 5). The magnitude of this effect is also similar to the one estimated in the urban form model (1.87% vs 2.28%).

- Spatial variation in employment has an indirect effect on traffic safety in the integrated model, however this factor had a direct and an indirect significant effect on traffic safety in the urban form model. A 10% reduction in the spatial variation of employment (a 10% increase in polycentricity) can decrease the rate of fatal crashes by 2.27%, indirectly through its effect on traffic congestion. This value is lower than its estimated effect on traffic safety in the urban form model (5.89%). It is worth mentioning that the larger the number of significant independent variables in a model, the smaller the magnitude of their effect on dependent variable. This can be a statistically reason for this difference (2.27% vs 5.89%).
- Income per capita, as a trip generation indicator, has an indirect significant effect on traffic safety. A 10% increase in income per capita is associate with a 4.6% increase in the rate of traffic crashes, indirectly by increasing the traffic congestion.
- Urban density has both direct and indirect effects on traffic safety. A 10% increase in urban density is associated with a 5.31% decrease in the risk of traffic crashes (4.08% directly + 1.23% indirectly). The estimated direct effect of this latent variable on traffic safety was 2.04% in the urban form model. This difference (5.31% vs 2.04%) is result of two causes: 1) urban density had only a direct significant effect in the urban form model, however it has both direct and indirect effects in the integrated model, and 2) the number of independent variables in the integrate model is more than in the urban form model.
- Day-time and night-time population density is effective on traffic safety, directly and indirectly. A 10% increase in population density can increase the incidence of traffic crashes by 6.05% directly and 7.3% indirectly.

- In-commuting flow of workers into the UA can directly increase the risk of fatal crashes. A 10% increase in the rate of in-commuting flow is associated with a 0.94% increase in the risk of fatal traffic crashes. This value is close to the one estimated in the chapter 6 for the trip generation model, 60%.
- Education is one of the most effective macro-level attributes to increase traffic safety in the integrated model, similar to the trip generation model. A 10% increase in the average number of years of education for the residents of a UA is associated with a 35% positive direct effect on traffic safety.
- Presence of heavy vehicles has a significant direct effect on traffic safety. A 10% decrease in the ratio of heavy vehicles on the road network can directly reduce the rate of fatal crashes by 3.01%. This value is less than the direct effect of heavy vehicles on traffic safety in the trip generation model (chapter 6), 4.63%.

7.3. Path Analysis: SEM – Integrated Model for Pedestrian Safety

The same set of hypothesized observed and latent independent variables and mediators tested in the model of overall traffic safety is also used to develop the integrated model for pedestrian safety. The hypothesized structure of this model is also the same, except that pedestrian safety (the observed variable of FPED: pedestrian fatalities) replaces the latent variable formed from the other five traffic safety attributes (FCRA, FATA, FPER, FVEH, and FDRU).

Figure 7.2 represents the final estimated integrated SEM model for pedestrian safety. Numerical values represent standardized coefficients of variables significant at 5% that construct the final PA. The statistical significance levels (p-value) under 0.01, and under 0.05 are shown by ** and *, respectively.

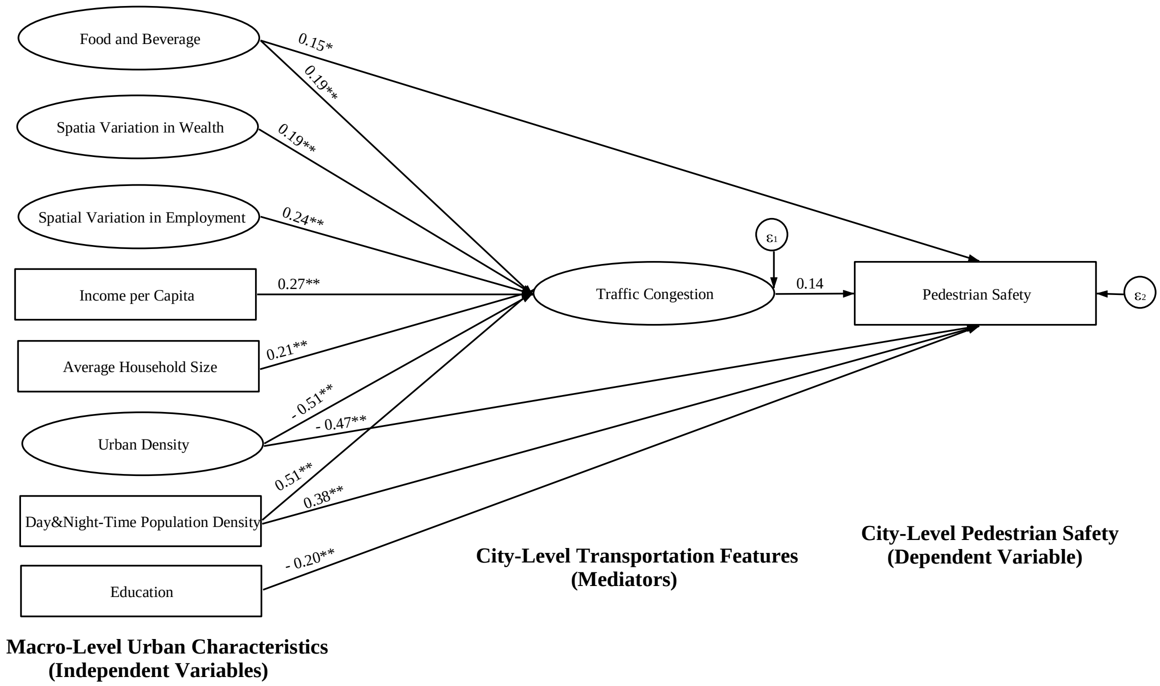

FIGURE 7.2: Integrated SEM model for pedestrian safety.

Table 7.2 reports on the sensitivity analysis of the estimated SEM model. The effect of a 10% change in observed variables and latent factors (simultaneous change in all observed variables forming each latent factor) on pedestrian safety, while other variables are kept constant, is reported in this table. A more complete version of this table is presented in the Appendix A.6.

TABLE 7.2. Sensitivity analysis – macro-level urban characteristics and pedestrian Safety

Independent Variable (Latent/Observed)	Change in Observed Independent Variables (%)		Effect Type	Associated Change in Observed FPED Dependent Variable (%)
	Variable	Change		
Food and Beverage	REPC	- 10	Direct	- 7.23
	BAPC	- 10		
	CAPC	- 10		
Food and Beverage	REPC	- 10	Indirect	- 1.89
	BAPC	- 10		
	CAPC	- 10		
Spatial Variation in Wealth	GIMI	- 10	Indirect	- 3.95
	GICO	- 10		
	INPC	- 10		
Spatial Variation in Employment	GIJW	- 10	Indirect	- 4.81
	GIJH	- 10		
	GIWP	- 10		
	POJP	- 10		
	EMJR	- 10		
	EMPC	- 10		
Income per Capita	INPC	- 10	Indirect	- 4.87
Average Household Size	AHHS	- 10	Indirect	- 4.12
Urban Density	COSM	+ 10	Direct	- 11.54
	PRSM	+ 10		
	FMSM	+ 10		
	NMSM	+ 10		
Urban Density	COSM	+ 10	Indirect	- 5.21
	PRSM	+ 10		
	FMSM	+ 10		
	NMSM	+ 10		
Day & Night-Time Population Density	COPRSM	- 10	Direct	- 17.11
Day & Night-Time Population Density	COPRSM	- 10	Indirect	- 7.73
Education	EDUC	+ 10	Direct	- 42.18

In relation to the objectives of this research, the main results derived from the model can be summarized as follows:

- Similar to the urban form and trip generation models (in chapters 5 and 6), the mediator in the integrated model is traffic congestion. The mediation effects of green transportation modes, walkability, and average commuting time are not statistically significant.
- Some statistically significant variables in the urban form and trip generation models have lost their significance in the integrated model, such as network connectivity, in-commuting flow, productivity, and recreation and services attractors. This can

be explained by existence of multicollinearity between studied independent variables in the integrated model.

- Food and beverage attraction has both direct and indirect effects on pedestrian safety. A 10% increase in the density of food and beverage attractions can increase the risk of fatal pedestrian crashes by 9.12% in total (7.23% directly + 1.89% indirectly). However, the compound reported effect of this factor in the trip generation model (chapter 6) was 23.2%. It is worth mentioning that the larger the number of significant independent variables in a model, the smaller the magnitude of their effect on dependent variable. This can be the statistically reason for this difference (9.12% vs 23.2%).
- Spatial variation in wealth has an indirect effect on pedestrian safety, same as in the urban form model (chapter 5). A more even spatial distribution of different social classes among different tracts of a UA decreases the traffic congestion, resulting in an increase in pedestrian safety. A 10% increase in even distribution of wealth among different tracks will increase pedestrian safety by 3.95%. The magnitude of this effect is different than the one estimated in the urban form model (3.95% vs 7.12%), resulted from the difference in the number of studied independent variables in two models.
- Spatial variation in employment has an indirect effect on pedestrian safety in the integrated model, same as with the urban form model. A 10% reduction in the spatial variation of employment (a 10% increase in polycentricity) can decrease the rate of pedestrian crashes by 4.81%, indirectly through its effect on traffic congestion. This value is lower than its estimated effect on pedestrian safety in the

urban form model (4.81% vs 5.48%). Because the number of significant independent variables in a model, the smaller the magnitude of their effect on the dependent variable.

- Income per capita, as a trip generation indicator, has an indirect significant effect on pedestrian safety. A 10% increase in income per capita is associate with a 4.87% increase in the rate of pedestrian crashes, indirectly by increasing the traffic congestion.
- Urban density has both direct and indirect effects on pedestrian safety. A 10% increase in urban density is associated with a 16.75% decrease in the risk of pedestrian crashes (11.54% directly + 5.21% indirectly).
- Similar to the trip generation model, day-time and night-time population density is directly and indirectly effective on pedestrian safety in the integrated mode as well. A 10% increase in population density can increase the incidence of pedestrian crashes by 17.11% directly and 7.73% indirectly.
- Education is one of the most effective macro-level attributes to increase pedestrian safety in the integrated model, similar to the trip generation model. A 10% increase in the average number of years of education for the residents of a UA is associated with a 42% positive direct effect on traffic safety.
- Average household size is another indirectly effective factor on traffic safety. Families with a higher household size have probably more kids and less access to passenger cars. Thus, UAs with higher AHHS are more prone to pedestrian crashes. A 10% increase in average household size is associated with a 4.12% increase in the rate of pedestrian fatalities. This value is lower than the estimated value in the

trip generation model (chapter 6), probably because there are more number of independent variables in the integrated model.

7.4. Conclusions

This chapter focused on the relationship between macro-level urban characteristic and traffic safety. The purpose of this chapter was to study the joint effect of urban form and trip generation characteristics on traffic safety. The previously introduced urban form indices and trip generation indicators as independent variables, the transportation network features as mediators and latent traffic and observed pedestrian safety variables are used to estimate the integrated models of traffic safety and pedestrian safety. Unlike the previous chapters, both overall traffic safety and pedestrian safety models have traffic congestion as their mediator variable.

Spatial distribution in employment has indirect effect on both overall traffic and pedestrian safety. More balanced and even job-housing spatial distribution in UAs, decreases traffic congestion, and consequently increases traffic and pedestrian safety.

Urban density is directly and indirectly effective on both overall traffic safety and pedestrian safety. Denser UAs are generally safer.

Spatial distribution of wealth is indirectly on both overall traffic safety and pedestrian safety. Even spatial distribution of different social classes among different tracts of a UA effectively reduces traffic congestion and consequently increases the overall traffic safety and the pedestrian safety indirectly.

Connectivity in transportation network increases traffic safety directly. Unlike chapter 5, no significant effect of this factor on pedestrian safety is found in this chapter. On the other hand, supply of transit and high-level transport infrastructures has lost its significance in the integrated model when compared to trip generation indicators.

Similar to the results in chapter 6, the presence of heavy vehicles on the road network and in-commuting flow of workers into the UA directly increase the risk of traffic fatalities.

Day-time and night-time population density (residential and employment density) is effective on traffic and pedestrian safety. Higher population density is associated with higher risk of traffic crashes, especially pedestrian crashes.

The density of food and beverage attractions is effective on both overall traffic safety and pedestrian safety. This factor was found effective only on pedestrian crashes in chapter 6. A higher density of food attractions is associated with an increase in pedestrian flow and also traffic congestion, and consequently increase the risk of traffic crashes, especially pedestrian crashes.

Surprisingly, the density of recreation and services attractions as well as religious organizations are not significant variables in the integrated models when compared to urban form indicators.

Household size and income per capita are two effective household characteristics that affect traffic safety. UAs with higher household size are more prone to traffic crashes, especially pedestrian crashes. UAs with higher income per capita are expected to have more economic activities, higher congestion and consequently higher overall traffic crashes and pedestrian crashes.

The level of education increases both traffic and pedestrian safety. As discussed in the previous chapter, this attribute requires further research in transportation planning and policy as it is a very large-scale human-related policy variable which is not directly controlled or influenced by transportation policy makers.

In summary, the results and recommendation are similar to the previous chapters (5 and 6). However, after joining the indicators of urban form and trip generation together, the number of studied independent variables has grown, which has led to some adjustments in the models; supply of transportation infrastructures, density of recreation and services attractions and also religious organizations are not significant anymore. The interpretation of other effective factors is still very similar to chapters 5 and 6.

CHAPTER 8: SUMMARY AND CONCLUSIONS

8.1. Introduction

This chapter discusses the contribution of this research to the relevant body of literature. The major results are then summarized and the recommendations for urban planners and traffic safety policy makers are presented as well. Finally, some suggestions for future studies are mentioned.

8.2. Contribution

The main contributions of this research are summarized as follows:

- Overall traffic safety and pedestrian safety are studied separately and then compared in this research. Since pedestrian issues are as important as traffic related issues in UAs, the comparison between these two types of models could be helpful for city planners.
- This research studies the effect of multiple major attributes of UAs on traffic safety, including urban form, trip generation indicators and transportation network features. In addition to specific models that focus on each set of attributes, an integrated model is also developed.
- While much research has studied the relationship between different urban characteristics and traffic safety, most of this work has considered micro-level characteristics (street- and community-level) only. This research tries to fill this gap in traffic safety literature where there are very few studies on macro-level (aggregate-level) urban features and city-level traffic safety.

- Another advantage of this research compared to the existing literature is to study a broad range of variables (e.g., city characteristics, transportation network characteristics and household information) for 100 UAs in the US. It is very crucial to collect such a reliable database for a large number of observations when defining consistent attributes for cities of different regions is a very critical task. Most of the existing literature suffers either from too small a sample size or from the lack of a broad range of consistent variables.
- The SEM technique used in this research is another promising contribution. The SEM is able to handle a very complex database with multiple interrelationships and direct and indirect relationships. Factor analysis helps to reduce the data by combining similar variables and making a new latent factor to represent them. Traffic safety in urban areas is a complex problem by nature involving multiple effective factors which can be modeled effectively by SEM approach.

8.3. Summary of Results

The main results of this research are summarized as follows:

- Encouraging the use of non-driving transportation modes (green transportation) is an effective policy to increase traffic safety overall.
- Controlling traffic congestion is an effective policy to increase pedestrian safety.
- A more even spatial distribution in job-housing balance increases the use of non-driving transportation modes and decreases traffic congestion. Thus, it increases both overall traffic safety and pedestrian safety.
- Urban density positively affects both overall traffic safety and pedestrian safety.

- The more even spatial distribution of different social classes among urban tracts increases both overall traffic safety and pedestrian safety.
- Connectivity in transportation network increases both overall traffic safety and pedestrian safety.
- Population density is directly associated with the risk of pedestrian crashes.
- The density of trip generators such as food and beverage outlets is associated with the incidence of pedestrian crashes.
- Providing more local services and amenities decreases pedestrian crashes.
- In-commuting flow of workers into the UA is associated with an increase in the risk of traffic crashes.
- An increased proportion of heavy vehicles on the transportation network increases the risk of traffic fatalities.
- Education is the most important human-related factor to increase both traffic safety and pedestrian safety and requires further research in the field of transportation policy making.

8.4. Synthesis

This section briefly addresses the main initial research questions.

- Urban form and traffic safety: urban form metrics affect both overall traffic safety and pedestrian safety significantly. Spatial variation in employment, urban density and urban connectivity are top three effective factors of urban form on transportation safety. Increase in urban polycentricity, decreases in urban sprawl and increased network connectivity can increase the overall traffic safety and pedestrian safety of UAs.

- Trip generation and traffic safety: trip generation indicators affects both overall traffic safety and pedestrian safety significantly. Density of urban amenities (food and beverage centers and recreation and services attractions), population density and level of education are the three most influential factors on transportation safety. Increase in the level of education, decreases in the density of non-local urban amenities and decreases in population density can increase the overall traffic safety and pedestrian safety.
- Integrated model versus specific models: the integrated model is as significant and meaningful as the specific models. The advantage of the integrated model is the opportunity to evaluate and rank the relative importance of all significant attributes.
- Overall traffic safety versus pedestrian safety: the main difference between overall and pedestrian safety is that the overall traffic safety can be increased by policies that encourage the use of non-driving transportation modes while the pedestrian safety can be increased by policies that control traffic congestion.

8.5. Recommendations

The top six recommendations for city planners are summarized as follows:

- Plan for polycentric urban designs with more even distribution of jobs across the UA.
- Plan to decrease urban sprawl and increase urban development density.
- Plan to provide more connection points and more accessibility in a UA.
- Plan for mixed land-use designs to provide more local access to daily-life trip attractors (e.g., food and beverage centers, religious organization, recreation and services).

- Plan to provide more public transit in the UA and encourage people to use non-driving transportation modes.
- Plan to control traffic congestion, especially by regulating the off-peak hours allowed time for heavy vehicles and changing the work schedule of workers who do not reside in the UA.

Figure 8.1 represents the estimated range of effects of the most effective macro-level urban policies to increase traffic safety.

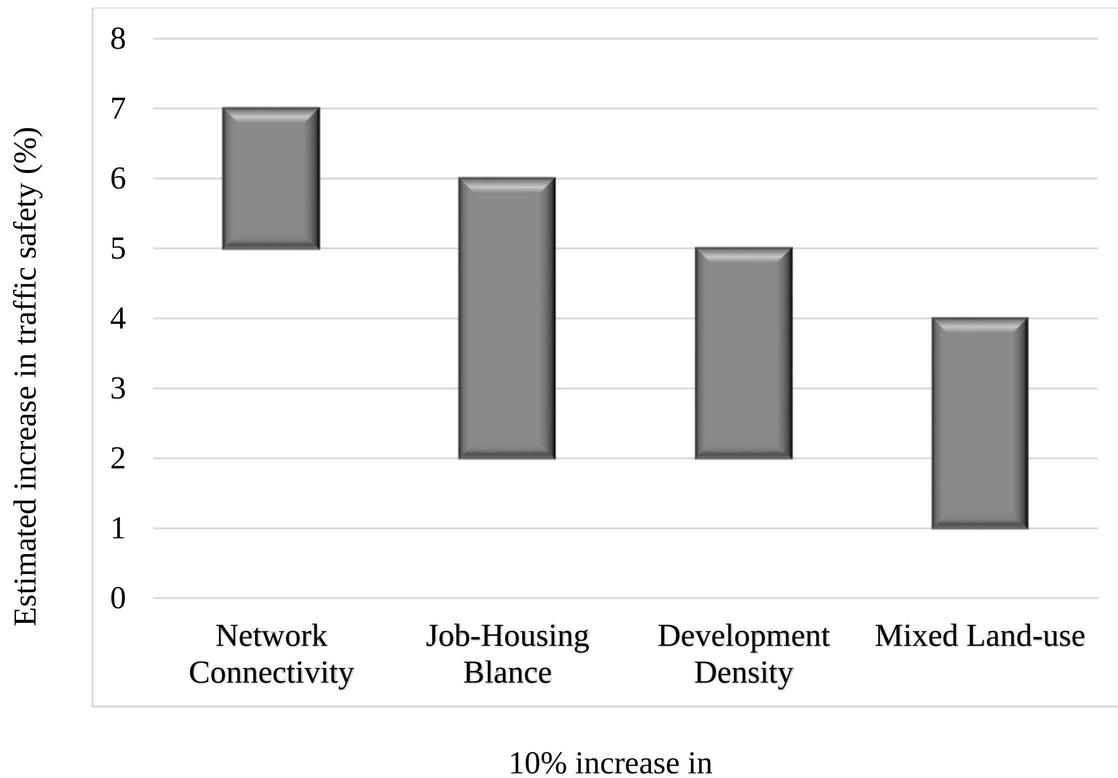

FIGURE 8.1: Effect of macro-level urban planning policies on traffic safety.

Figure 8.2 visualizes some of the most efficacious urban planning factors to increase traffic safety.

FIGURE 8.2: Urban planning implications to increase traffic safety.

8.6. Suggestions for Future Research

The investigation conducted for this dissertation has identified a new line of research that uncovered significant and meaningful factors of traffic safety at the scale of cities. Limitations have been identified. The most important suggestion to overcome these limitations is in the area of data availability. First of all, there is almost no national-wide dataset on non-fatal crashes. It is strongly recommended that USDOT collects consistent data for injury and non-injury traffic crashes in UAs to enable to broaden the scope of metrics of traffic safety. Having information for non-fatal crashes will make it possible to study the effect of different factors on the severity of traffic crashes in addition to the crash rate.

In addition, it is strongly suggested that DOTs define consistent macro-level indicators for UAs. For instance, DOTs can define the index of safety, accessibility, connectivity, sprawl or density based on a consistent methodology for different UAs. These consistent metrics can be very useful for researchers and practitioners to study different aspects of transportation planning in UAs.

Furthermore, it is suggested that collecting consistent information for a large number of UAs can improve the statistical validity of the models. Additionally, including other macro-level urban features (e.g., geographic, social and economic characteristics) would help in gaining a more complete picture of the determinants of traffic safety. Finally, temporal and spatial validation on the results (e.g., performing a before-after study) can be very interesting.

REFERENCES

1- Road Safety. Roads and Highways. Working for a World Free of Poverty. (2015). World Bank. Retrieved June 5, 2015, from worldbank.org/transport/roads/safety.htm

2- General statistics. (2013). Insurance Institute for Highway Safety. Retrieved June 5, 2015, from iihs.org/iihs/topics/t/general-statistics/fatalityfacts/overview-of-fatality-facts/2013

3- Blincoe, L. J., Miller, T. R., Zaloshnja, E., & Lawrence, B. A. (2015). The Economic and Societal Impact of Motor Vehicle Crashes (2010, Revised). Washington, DC, National Highway Traffic Safety Administration

4- Najaf, P., Isaai, M.T., Lavasani, S.M., & Thill, J.C. (2016). Evaluating Traffic Safety Policies for Developing Countries Based on Equity Considerations, Journal of Transportation Safety and Security, dx.doi.org/10.1080/19439962.2016.1230163

5- AAA Study Finds Costs Associated With Traffic Crashes Are More than Three Times Greater than Congestion Costs. NewsRoom. Retrieved July 7, 2015, from newsroom.aaa.com/2011/11/aaa-study-finds-costs-associated-with-traffic-crashes-are-more-than-three-times-greater-than-congestion-costs/

6- Morbidity and Mortality Weekly Report 2009: Motor Vehicle Crash Deaths in Metropolitan Areas - United States. (2012). Center for Disease Control and Prevention. 523-528. Retrieved from cdc.gov/mmwr/preview/mmwrhtml/mm6128a2.htm

7- 2010 Census U.S. Census Bureau. (2010). United States Census Bureau.

8- Dalkmann, H., & Irigoyen, J. L. Want Healthy, Thriving Cities? Tackle Traffic Safety First. World Resources Institute. Retrieved from wri.org/blog/2015/01/want-healthy-thriving-cities-tackle-traffic-safety-first

9- Portland Plan: Comprehensive Plan Evaluation. Urban Form Technical Working Group.

10- Introduction to Urban Form and Transportation. City Subjects. Retrieved from cityobservatory.org/urban-form-and-trans/

11- Dumbaugh, E., & Rae, R. (2009). Safe Urban Form: Revisiting the Relationship between Community Design and Traffic Safety. Journal of the American Planning Association, 75(3), 309–329. doi:10.1080/01944360902950349

12- Adriazola, C., & Colin, B. More Urbanites, More Cars: The Challenge of Urban Road Safety and Health. World Resources Institute. Retrieved from wri.org/blog/2013/02/more-urbanites-more-cars-challenge-urban-road-safety-and-health

13- Khabazi, M., & Foroughmand, H. (2011). The Role of Urban Design in Achieving Sustainability through Promotion of Sustainable Behaviors (case study: Melat Park in Tehran Iran). 5th Conference of the International Forum on Urbanism (IFOU), Tehran, Iran

14- The Role of Sustainable Transport in Traffic Safety. EMBARQ.

15- Planning for Pedestrians in Large Urban Centers. (pp. 119–182). Retrieved from home.earthlink.net/~schallerconsult/data/lcchp3.pdf

16- Traffic Safety Facts: 2013 Data. (2015). National highway Traffic Safety Administration. Washington, DC.

17- A Primer on Safety Performance Measures for the Transportation Planning Process: What Are Safety Performance Measures? (2014). Federal highway Administration.

18- Jones, D., & Jha, M. K. (2009). The Effect of Urban Form on Traffic Accident Incidence. Recent Advances in Computer Engineering and Applications, 212–222.

19- Mashayekhi, M., & List, G. (2015). A multi-agent auction-based approach for modeling of signalized intersections. Workshop on Synergies Between Multiagent Systems, Machine Learning and Complex Systems

20- Fundamentals of Transportation/Trip Generation. WIKIBOOKS. Retrieved February 2, 2016, from en.wikibooks.org/wiki/Fundamentals_of_Transportation/Trip_Generation

21- Trip Generation/Production. Caliper: Mapping & Transportation Software Solutions. Retrieved February 2, 2016, from caliper.com/uk/trip_generation.htm

22- Trip Generation Discussion Working Paper: An Overview of Trip Generation.

23- Ghahramani, N., & Brakewood, C. (2016). Trends in Mobile Transit Information Utilization: An Exploratory Analysis of Transit App in New York City. Journal of Public Transportation, 19(3), 139-160.

24- Handy, S., Shafizadeh, K., & Schneider, R. California Smart-Growth Trip Generation Rates Study. University of California, Davis for the California Department of Transportation.

25- Tripi, E. J. (2011). Basics of ITE Trip Generation and ITS Role in Calculating Transportation Impact Fees. In 2011 Growth and Infrastructure Consortium Conference.

26- Schneider, R. J., Handy, S. L., & Shafizadeh, K. (2014). Trip Generation for Smart Growth Projects. Access, 45, 9–15.

27- Khabazi, M., & Isabelle, N. (2016). Spatial Interaction among Retail Chains: City Characteristics and Zoning Practices. AAG Annual Meeting, San Francisco, US.

28- Sorratini, J. A., & Soares de Andrade, C. P. Characteristics of the Trips Generated by a Trip Generation HUB. In 10th International Conference on Computers in Urban Planning and Urban Management.

29- Gulden, J., Goates, J., & Ewing, R. (2013). Mixed-Use Development Trip Generation Model. University of Utah.

30- Fatality Analysis Reporting System (FARS). National Highway Traffic Safety Administration.

31- Lord, D., & Persaud, B. N. (2004). Estimating the Safety Performance of Urban Road Transportation Networks, 36, 609–620. doi:10.1016/S0001-4575(03)00069-1

32- Pedestrian and Bicyclist Crash Statistics. Pedestrian and Bicycle Information Center.

33- Bento, A. M., Cropper, M. L., Mobarak, A. M., & Vinha, K. (2003). The Impact of Urban Spatial Structure on Travel Demand in the United States. The World Bank Development Research Group.

34- Bento, A. M., Cropper, M. L., Mobarak, A. M., & Vinha, K. (2005). The Effect of Urban Spatial Structure on Travel Demand in the United States. The Review of Economics and Statistics, 87(August), 466–478.

35- Urban Form and Neighborhood Design. In On-Line Edition of the General Plan Framework. Los Angeles, CA: Planning Department Central Publications.

36- Mohan, D. (2008). Traffic Safety and City Structure: Lessons for the Future. Salud Pública Méx, 50.

37- Nassiri, H., Najaf, P., & Mohammadian, A. (2014). Prediction of Roadway Accident Frequencies: Count Regressions versus Machine Learning Models. Scientia Iranica-Transaction A: Civil Engineering, 21 (2), 263-275.

38- Ewing, R., & Dumbaugh, E. (2009). The Built Environment and Traffic Safety: A Review of Empirical Evidence. Journal of Planning Literature, 23(4), 347–367.

39- Five Ways to Save Lives with Urban Design. (2015). Sustainable Cities Collective. Retrieved from sustainablecitiescollective.com/dirt/1091297/saving-lives-urban-design

40- Dora, C., Hosking, J., & Mudu, P. Urban Transport and Health: Sustainable Transport- A Sourcebook for Policy Makers in Developing Cities.

41-Alonso, W. (1964). *Location and Land Use: Toward a General Theory of Land Rent*. Harvard University Press, Cambridge, MA.

42- Lin, D., Allan, A., Cui, J., & McLaughlin., R. (2012). The Effects of Polycentric Development on Commuting Patterns in Metropolitan Areas. Regional Studies Association: Global Conference 2012, Los Angeles.

43- Ewing, R., Schieber, R. A., & Zegeer, C. V. (2003). Urban Sprawl as a Risk Factor in Motor Vehicle Occupant and Pedestrian Fatalities. American Journal of Public Health, 93(9), 1541–1545.

44- Ewing, R., Hamidi, S., & Grace, J.B. Urban Sprawl as A Risk Factor in Motor Vehicle Crashes. Urban Studies, 53(2), 247-266.

45- Frumkin, H. (2002). Urban Sprawl and Public Health. Public Health Report, 17, 201–217.

46- Redelmeier, D. A., Tibshiran, R. J., Evans, L., & Phil, D. (2003). Traffic-Law Enforcement and Risk of Death from Motor-Vehicle Crashes: Case-Crossover Study. The Lancet, 361, 2177–2182.

47- Abdel-Aty, M., Siddiqui, C., Huang, H., & Wang, X. (2011). Integrating Trip and Roadway Characteristics to Manage Safety in Traffic Analysis Zones. Transportation Research Record: Journal of the Transportation Research Board, No. 2213, 20–28. doi:10.3141/2213-04

48- Pulugurtha, S. S., Ramana, V., & Kotagiri, Y. (2013). Traffic Analysis Zone Level Crash Estimation Models Based on Land Use Characteristics. Accident Analysis and Prevention, 50, 678–687. doi:10.1016/j.aap.2012.06.016

49- Johannesson, M., Johansson, P.-O., & O'conor, R. M. (1996). The Value of Private Safety versus the Value of Public Safety. Journal of Risk and Uncertainty, 13, 263–275.

50- Nantulya, V. M., & Reich, M. R. (2003). Equity Dimensions of Road Traffic Injuries in Low- and Middle-Income Countries. Injury Control and Safety Promotion, 10(1-2), 13–20. doi:10.1076/icsp.10.1.13.14116

51- Fayyaz Shahandashti, S.K., Liu, X.C., & Porter, R.J. (2016). A Genetic-Algorithm and Regression-Based Model for Analyzing Fare Payment Structure and Transit Dwell Time. Transportation Research Board 95th Annual Meeting, Washington DC.

52- Partyka, S. C. (1984). Simple Models of Fatality Trends Using Employment and Population Data. Accident Analysis and Prevention, (3), 211–222.

53- Isaai, M.T., Najaf, P., Lavasani, S.M., & Nezamianpour, H. (2013). Intelligent Evaluation of Transportation Management Policies for Metropolitan Areas. Transportation Research Board Annual Meeting, Washington, D.C.

54- Fields, M. G. (2015). The Correlates of Congestion: Investigating the Links between Congestion and Urban Area Characteristics. PhD Dissertation. Department of Geography and Earth Sciences, University of North Carolina at Charlotte.

55- Kopits, E., & Cropper, M. (2005). Traffic Fatalities and Economic Growth. Accident Analysis and Prevention, 37, 169–178. doi:10.1016/j.aap.2004.04.006

56- Christie, N. (1995). The High Risk Child Pedestrian: Socio-Economic and Environmental Factors in Their Accidents. Transport Research Laboratory (Great Britain).

57- Factor, R., Mahalel, D., & Yair, G. (2008). Inter-Group Differences in Road-Traffic Crash Involvement. Accident Analysis and Prevention, 40(6), 2000–2007.

58- Dandona, R., Kumar, G. A., Raj, T. S., & Dandona, L. (2006). Patterns of Road Traffic Injuries in a Vulnerable Population in Hyderabad, India. Injury Prevention, 12, 183–188.

59- Treno, A. J., Johnson, F. W., Remer, L. G., & Gruenewald, P. J. (2007). The Impact of Outlet Densities on Alcohol-Related Crashes: A Spatial Panel Approach. Accident Analysis and Prevention, 39, 894–901. doi:10.1016/j.aap.2006.12.011

60- Dejoy, M. (1992). An Examination of Gender Differences Traffic Accident Risk Perception. Accident Analysis and Prevention, 24(3), 237–246.

61- Zhang, J., Fraser, S., Lindsay, J., Clarke, K., & Mao, Y. (1998). Age-specific Patterns of Factors Related to Fatal Motor Vehicle Traffic Crashes: Focus on Young and Elderly

Drivers. Public Health, 112, 289–295.

62- Schiff, M., & Becker, T. (1996). Trends in Motor Vehicle Traffic Fatalities among Hispanics, Non-Hispanic Whites and American Indians in New Mexico, 1958–1990. Ethnicity & Health, 1(3).

63- Romano, E., Tippetts, S., & Voas, R. (2005). Fatal Red Light Crashes: The Role of Race and Ethnicity. Accident Analysis and Prevention, 37(December 2004), 453–460. doi:10.1016/j.aap.2004.12.006

64- Levy, D. T. (1990). Youth and Traffic Safety: The Effects of Driving age, Experience and Education. Accident Analysis and Prevention, 22(4), 327–334.

65- Harrington, D. M., & Mcbride, R. S. (1970). Traffic Violations by Type, Age, Sex, and Marital Status. Accident Analysis and Prevention, 2.

66- Lagarde, E., Chastang, J. F., Gueguen, A., Coeuret-Pellicer, M., Chiron, M., & Lafont, S. (2004). Emotional Stress and Traffic Accidents: The Impact of Separation and Divorce. Epidemiology, 15(6), 762–766.

67- Kim, K., Brunner, I. M., & Yamashita, E. Y. (2006). Influence of Land Use, Population, Employment, and Economic Activity on Accidents. Transportation Research Record: Journal of the Transportation Research Board, (1953), 56–64.

68- Loukaitou-sideris, A., Liggett, R., & Sung, H.-G. (2012). Death on the Crosswalk: A Study of Pedestrian-Automobile Collisions in Los Angeles. Journal of Planning Education and Research, 338–351. doi:10.1177/0739456X06297008

69- Alsop, J., & Langley, J. (2001). Under-Reporting of Motor Vehicle Traffic Crash Victims in New Zealand. Accident Analysis and Prevention, 33, 353–359.

70- Joly, M., Fcggin, P. M., & Pless, B. (1991). Geographical and Socio-Ecological Variations of Traffic. Social Science & Medicine, 33(7), 765–769.

71- Moghaddam, F.R., Afandizadeh, SH., & Ziyadi. M. (2011). Prediction of Accident Severity Using Artificial Neural Networks. International Journal of Civil Engineering, 9(1), 41-49.

72- Andreyl, J., & Olley, R. (1990). Relationships between Weather and Road Safety: Past and Future Research Directions. Climatological Bulletin, 24(3), 123–137.

73- Kermanshah, M., Najaf, P., & Nezamianpour, H. (2012). Developing Nested Logit

Probability Models for Rollover Accident Occurrence and Driver Injury Severity. Transportation Research Journal, 1, 35-45.

74- Moghimidarzi, S.B., Furth, P.G., & Cesme, B. (2016). Predictive–Tentative Transit Signal Priority with Self-Organizing Traffic Signal Control. Transportation Research Record: Journal of the Transportation Research Board, Volume 2557, 77-85.

75- Keall, D. M. (1995). Pedestrian Exposure to Risk of Road Accident in New Zealand. Accident Analysis and Prevention, 27(5), 729–740.

76- Chang, L., & Mannering, F. (1999). Analysis of Injury Severity and Vehicle Occupancy in Truck- and Non-Truck-Involved Accidents. Accident Analysis and Prevention, 31, 579–592.

77- Marshall, W. E., & Garrick, N. W. (2011). Does Street Network Design Affect Traffic Safety? Accident Analysis and Prevention, 43(3), 769–781.

78- Cottrill, C. D., & Thakuriah, P. (2010). Evaluating Pedestrian Crashes in Areas with High Low-Income or Minority Populations. Accident Analysis and Prevention, 42(6), 1718–1728.

79- Chang, L. (2005). Analysis of Freeway Accident Frequencies: Negative Binomial Regression versus Artificial Neural Network. Safety Science, 43, 541–557. doi:10.1016/j.ssci.2005.04.004

80- Babazadeh, A., Langerudi, M. F., Afkar, N., & Fayyaz Shahandashti, S.K. (2014). Parameter Selection in Particle Swarm Optimization For Transportation Network Design Problem, Journal of Computing Research Repository (CoRR)

81- Quddus, M. A., Wang, C., & Ison, S. G. (2010). Road Traffic Congestion and Crash Severity: Econometric Analysis Using Ordered Response Models. Journal of Transportation Engineering, 136, 424–435.

82- Golob, T. F., Recker, W. W., & Alvarez, V. M. (2004). Freeway Safety as a Function of Traffic Flow. Accident Analysis and Prevention, 36(6), 933–946.

83- Tabatabaee, N., Ziyadi, M., & Shafahi, Y. (2013). Two-Stage Support Vector Classifier and Recurrent Neural Network Predictor for Pavement Performance Modeling. Journal of Infrastructure Systems, 19(3), 266-274.

84- Tighe, S., Li, N., Falls, L. C., & Haas, R. (2000). Incorporating Road Safety into Pavement Management. Transportation Research Record: Journal of the Transportation

Research Board, 1699, 1–10.

85- Mayora, J. M., & Pina, R. J. (2009). An Assessment of the Skid Resistance Effect on Traffic Safety under Wet-Pavement Conditions. Accident Analysis and Prevention, 41(4), 881–886.

86- Badland, H., & Schofield, G. (2005). Transport, Urban Design, and Physical Activity: An Evidence-Based Update. Transportation Research Part D, 10, 177–196. doi:10.1016/j.trd.2004.12.001

87- Alluri, P., Haleem, K., Gan, A., Lavasani, M., & Saha, D. (2013). Comprehensive Study to Reduce Pedestrian Crashes in Florida, Florida Department of Transportation

88- Pedestrians Synthesis Report. United States Department of Transportation.

89- Fartash, H., Alluri, P., Gan, A., Lavasani, M., & Haleem, K. (2016). Performance of Rectangular Rapid Flashing Beacons at Midblock Pedestrian Crossings. Transportation Research Board 95th Annual Meeting, Washington, D.C.

90- Bowman, B. L., & Vecellio, R. L. (1994). Effect of Urban and Suburban Median Types on both Vehicular and Pedestrian Safety. Transportation Research Record: Journal of the Transportation Research Board, 1445, 169–179.

91- Stoker, P., Garfinkel-Castrol, A., Khayesi, M., Odero, W., Mwangi, M.N., Peden, M., &Ewing, R. Pedestrian Safety and the Built Environment: A Review of the Risk Factors. Journal of Planning Literature, 2015, 30(4), 377-392.

92- Najaf, P., & Pulugurtha, S.S. (2014), Efficiency and Safety Evaluation of Unconventional Intersections, 8th National Congress on Civil Engineering, Iran.

93- Handy, S. (2014). Urban Form and Pedestrian Choices: Study of Austin Neighborhoods. Transportation Research Record: Journal of the Transportation Research Board, 1552.

94- Heath, G. W., Brownson, R. C., Kruger, J., Miles, R., Kenneth, E., Ramsey, L. T., … Ramsey, L. T. (2006). The Effectiveness of Urban Design and Land Use and Transport Policies and Practices to Increase Physical Activity: A Systematic Review. Journal of Physical Activity and Health, 3(1), 55–76.

95- Graham, D. J., & Glaister, S. (2003). Spatial Variation in Road Pedestrian Casualties: The Role of Urban Scale, Density and Land-use Mix. Urban Studies, 40(8), 1591–1607. doi:10.1080/0042098032000094441

96- Dumbaugh, E., & Li, W. (2010). Designing for the Safety of Pedestrians, Cyclists, and Motorists in Urban Environments. Journal of the American Planning Association, 77(1), 69–87. doi:10.1080/01944363.2011.536101

97- Annual Urban Mobility Report. (2010). Texas A&M Transportation Mobility Institute.

98- City Data. (2015). Retrieved from city-data.com

99- Find the Home. (2015). Retrieved from places.findthehome.com

100- American Community Survey (ACS). (2012). Retrieved from census.gov/programs-surveys/acs/data.html

101- TransCAD Transportation Planning Software. Caliper Corporation.

102- World Statesmen Organization. (2015). Retrieved from worldstatesmen.org

103- National Climate Data Center (NOAA). The United States National Centers for Environmental Information (NCEI).

104- Annual Demographia International Housing Affordability Survey. Retrieved from demographia.com/

105- Brookings Institute Report. (2010). Retrieved from brookings.edu/research/reports

106- U.S. Bureau of Economic Analysis (BEA). U.S. Department of Commerce. Retrieved from bea.gov

107- Federal Highway Administration Research and Technology (FHWA). (2010). U.S. Department of Transportation.

108- Walk Score, 2016, walkscore.com.

109- Redfin. How Walk Score Works, redfin.com/how-walk-score-works.

110- Long-Term Pavement Performance Studies. LTPP InfoPave. Retrieved from infopave.com

111- National Transit Database. Retrieved from ntdprogram.gov/ntdprogram/data.htm

112- Wang, K., & Qin, X. (2014). Use of Structural Equation Modeling to Measure Severity of Single-Vehicle Crashes. Transportation Research Record: Journal of the Transportation Research Board, 2432, 17–25.

113- Suhr, D. (2006). Exploratory or Confirmatory Factor Analysis. In SAS Users Group International Conference (pp. 1–17). Cary: SAS Institute.

114- Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the Use of Exploratory Factor Analysis in Psychological Research. Psychological Methods, 4(3), 272–299.

115- Exploratory Factor Analysis. Statistics Solutions. Retrieved April 4, 2016, from statisticssolutions.com/factor-analysis-sem-exploratory-factor-analysis/

116- What Are the Differences between Factor Analysis and Principal Component Analysis? StackExchange. Retrieved March 3, 2016, from stats.stackexchange.com/questions/1576/what-are-the-differences-between-factor-analysis-and-principal-component-analysi

117- Confirmatory Factor Analysis. Statistics Solutions. Retrieved May 3, 2016, from statisticssolutions.com/confirmatory-factor-analysis/

118- Bowen, N. K., & Gua, S. (2011). Structural Equation Modeling. Oxford University Press.

119- Bollen, K. A. (1987). Total, Direct, and Indirect Effects in Structural Equation Models. Oxford University Press, 37–69.

120- Hox, J. J., & Bechger, T. M. (1998). An Introduction to Structural Equation Modeling. Family Science Review, 11, 354–373.

APPENDIX A: SENSITIVITY ANALYSIS – TABLES

TABLE A.1: Complete sensitivity analysis – urban form and traffic safety

Independent Variable (Latent)	Change in Observed Independent Variables (%)		Effect Type	Coefficient (Unstandardized)	Associate Change in Latent Dependent Variable	Associated Change in Observed Dependent Variables (%)	
	Variable	Change				Variable	Effect
Spatial Variation in Employment	GIJW	- 10	Direct	3.585	- 0.234	FCRA	- 3.26
	GIJH	- 10				FATA	- 3.18
	GIWP	- 10				FPER	- 3.22
	POJP	- 10				FVEH	- 3.23
	EMJR	- 10				FDRU	- 2.73
	EMPC	- 10					
Spatial Variation in Employment	GIJW	- 10	Indirect	- 3.562 × - 0.810	- 0.189	FCRA	- 2.63
	GIJH	- 10				FATA	- 2.57
	GIWP	- 10				FPER	- 2.60
	POJP	- 10				FVEH	- 2.61
	EMJR	- 10				FDRU	- 2.20
	EMPC	- 10					
Urban Density	COSM	+ 10	Direct	-0.001	- 0.146	FCRA	- 2.04
	PRSM	+ 10				FATA	- 1.99
	FMSM	+ 10				FPER	- 2.01
	NMSM	+ 10				FVEH	- 2.02
						FDRU	- 1.71
Spatial Variation in Wealth	GIMI	+ 10	Indirect	14.92 × - 0.810	- 0.163	FCRA	- 2.28
						FATA	- 2.22
	GICO	+ 10				FPER	- 2.24
	INPC	+ 10				FVEH	- 2.25
						FDRU	- 1.90
Supply of Transportation Infrastructures	GIPO	+ 10	Indirect	0.094 × - 0.810	- 0.145	FCRA	- 2.02
	GIWO	+ 10				FATA	- 1.98
	FLMN	+ 10				FPER	- 1.99
	TVPC	+ 10				FVEH	- 2.00
						FDRU	- 1.69
Network Connectivity	NLNN	+ 10	Indirect	7.77 × - 0.810	- 0.124	FCRA	- 1.73
						FATA	- 1.69
	NONM	+ 10				FPER	- 1.71
	NOSM	+ 10				FVEH	- 1.71
						FDRU	- 1.45

TABLE A.2: Complete sensitivity analysis – urban form and pedestrian safety

<table>
<tr><th rowspan="2">Independent Variable (Latent)</th><th colspan="2">Change in Observed Independent Variables (%)</th><th rowspan="2">Effect Type</th><th rowspan="2">Coefficient (Unstandardized)</th><th rowspan="2">Associate Change in Latent Dependent Variable</th><th colspan="2">Associated Change in Observed Dependent Variables (%)</th></tr>
<tr><th>Variable</th><th>Change</th><th>Variable</th><th>Effect</th></tr>
<tr><td rowspan="6">Spatial Variation in Employment</td><td>GIJW</td><td>- 10</td><td rowspan="6">Indirect</td><td rowspan="6">0.163 × 13.074</td><td rowspan="6">- 0.139</td><td rowspan="6">FPED</td><td rowspan="6">- 5.48</td></tr>
<tr><td>GIJH</td><td>- 10</td></tr>
<tr><td>GIWP</td><td>- 10</td></tr>
<tr><td>POJP</td><td>- 10</td></tr>
<tr><td>EMJR</td><td>- 10</td></tr>
<tr><td>EMPC</td><td>- 10</td></tr>
<tr><td rowspan="3">Spatial Variation in Wealth</td><td>GIMI</td><td>- 10</td><td rowspan="3">Indirect</td><td rowspan="3">1.027 × 13.074</td><td rowspan="3">- 0.181</td><td rowspan="3">FPED</td><td rowspan="3">- 7.12</td></tr>
<tr><td>GICO</td><td>- 10</td></tr>
<tr><td>INPC</td><td>- 10</td></tr>
<tr><td rowspan="4">Supply of Transportation Infrastructures</td><td>GIPO</td><td>- 10</td><td rowspan="4">Indirect</td><td rowspan="4">0.004 × 13.074</td><td rowspan="4">- 0.099</td><td rowspan="4">FPED</td><td rowspan="4">- 3.92</td></tr>
<tr><td>GIWO</td><td>- 10</td></tr>
<tr><td>FLMN</td><td>- 10</td></tr>
<tr><td>TVPC</td><td>- 10</td></tr>
<tr><td rowspan="3">Network Connectivity</td><td>NLNN</td><td>+ 10</td><td rowspan="3">Direct</td><td rowspan="3">- 23.052</td><td rowspan="3">- 0.453</td><td rowspan="3">FPED</td><td rowspan="3">- 17.85</td></tr>
<tr><td>NONM</td><td>+ 10</td></tr>
<tr><td>NOSM</td><td>+ 10</td></tr>
</table>

TABLE A.3: Complete sensitivity analysis – trip generation and traffic safety

Independent Variable (Latent/Observed)	Change in Observed Independent Variables (%)		Effect Type	Coefficient (Unstandardized)	Associate Change in Latent Dependent Variable	Associated Change in Observed Dependent Variables (%)	
	Variable	Change				Variable	Effect
Presence of Heavy Vehicles	HEVE	- 10	Direct	0.419	- 0.332	FCRA	- 4.63
						FATA	- 4.52
						FPER	- 4.57
						FVEH	- 4.59
						FDRU	- 3.88
In-Commuting Flow per Workers	COFW	- 10	Direct	0.078	- 0.043	FCRA	- 0.60
						FATA	- 0.58
						FPER	- 0.59
						FVEH	- 0.59
						FDRU	- 0.50
Percentage Change in Population	POPP	- 10	Indirect	- 0.018 × - 1.183	- 0.037	FCRA	- 0.52
						FATA	- 0.51
						FPER	- 0.52
						FVEH	- 0.52
						FDRU	- 0.44
Productivity	GDPP	+ 10	Direct	- 0.685	- 0.431	FCRA	- 5.99
						FATA	- 5.85
	EMPC	+ 10				FPER	- 5.91
	PAPW	+ 10				FVEH	- 5.93
						FDRU	- 5.02
Food and Beverage	REPC	- 10	Direct	0.074	- 0.197	FCRA	- 2.74
						FATA	- 2.68
	BAPC	- 10				FPER	- 2.70
	CAPC	- 10				FVEH	- 2.71
						FDRU	- 2.29
Food and Beverage	REPC	+ 10	Indirect	0.064 × - 1.183	- 0.201	FCRA	- 2.80
						FATA	- 2.74
	BAPC	+ 10				FPER	- 2.77
	CAPC	+ 10				FVEH	- 2.78
						FDRU	- 2.35
Recreation and Services Attraction	FCPC	- 10	Indirect	- 0.183 × - 1.183	- 0.027	FCRA	- 0.37
	YSPC	- 10				FATA	- 0.36
	VIPC	- 10				FPER	- 0.37
	AMPC	- 10				FVEH	- 0.37
						FDRU	- 0.31
Percentage of Unemployment	UEMP	+ 10	Indirect	0.076 × - 1.183	- 0.103	FCRA	- 1.44
						FATA	- 1.41
						FPER	- 1.42
						FVEH	- 1.43
						FDRU	- 1.20
Income per Capita	INPC	- 10	Direct	0.0001	- 0.273	FCRA	- 3.81
						FATA	- 3.72
						FPER	- 3.76
						FVEH	- 3.77
						FDRU	- 3.19
Income per Capita	INPC	+ 10	Indirect	0.0001 × - 1.183	- 0.324	FCRA	- 4.51
						FATA	- 4.40
						FPER	- 4.45
						FVEH	- 4.46
						FDRU	- 3.77
Religious Organizations per Capita	ROPC	- 10	Direct	0.078	- 0.163	FCRA	- 2.27
						FATA	- 2.21
						FPER	- 2.24
						FVEH	- 2.24
						FDRU	- 1.90
Religious Organizations per Capita	ROPC	- 10	Indirect	- 0.033 × - 1.183	- 0.082	FCRA	- 1.13
						FATA	- 1.11
						FPER	- 1.12
						FVEH	- 1.12

						FDRU	- 0.95
Education	EDUC	+ 10	Direct	- 1.071	- 1.408	FCRA	- 19.60
						FATA	- 19.14
						FPER	- 19.33
						FVEH	- 19.40
						FDRU	- 16.40
Education	EDUC	+ 10	Indirect	0.25 × - 1.183	- 0.388	FCRA	- 5.41
						FATA	- 5.29
						FPER	- 5.34
						FVEH	- 5.36
						FDRU	- 4.53

TABLE A.4: Complete sensitivity analysis – trip generation and pedestrian safety

Independent Variable (Latent/Observed)	Change in Observed Independent Variables (%)		Effect Type	Coefficient (Unstandardized)	Associate Change in Latent Dependent Variable	Associated Change in Observed Dependent Variables (%)	
	Variable	Change				Variable	Effect
In-Commuting Flow per Workers	COFW	- 10	Direct	0.057	- 0.031	FPED	- 1.24
Day & Night-Time Population Density	COPRSM	- 10	Direct	0.0001	- 0.043	FPED	- 1.71
Day & Night-Time Population Density	COPRSM	- 10	Indirect	0.00001 × 16.644	- 0.072	FPED	- 2.85
Food and Beverage	REPC	- 10	Direct	0.188	- 0.501	FPED	- 19.69
	BAPC	- 10					
	CAPC	- 10					
Food and Beverage	REPC	- 10	Indirect	0.002 × 16.644	- 0.088	FPED	- 3.49
	BAPC	- 10					
	CAPC	- 10					
Recreation and Services Attraction	FCPC	+ 10	Direct	- 0.532	- 0.065	FPED	- 2.58
	YSPC	+ 10					
	VIPC	+ 10					
	AMPC	+ 10					
Recreation and Services Attraction	FCPC	+ 10	Indirect	- 0.017 × 16.644	- 0.035	FPED	- 1.37
	YSPC	+ 10					
	VIPC	+ 10					
	AMPC	+ 10					
Average Household Size	AHHS	- 10	Direct	3.164	- 0.797	FPED	- 31.37
Income per Capita	INPC	- 10	Indirect			FPED	- 1.79
Religious Organizations per Capita	ROPC	+ 10	Direct	- 0.96	- 0.201	FPED	- 7.89
Education	EDUC	+ 10	Direct	- 1.262	- 1.659	FPED	- 65.32

TABLE A.5: Complete sensitivity analysis – macro-level urban characteristics and traffic safety

Independent Variable (Latent/Observed)	Change in Observed Independent Variables (%)		Effect Type	Coefficient (Unstandardized)	Associate Change in Latent Dependent Variable	Associated Change in Observed Dependent Variables (%)	
	Variable	**Change**				**Variable**	**Effect**
Single Occupancy Vehicles	SOVP	- 10	Direct	0.253	- 1.970	FCRA	- 27.41
						FATA	- 26.77
						FPER	- 27.04
						FVEH	- 27.14
						FDRU	- 22.94
Network Connectivity	NLNN	+ 10	Direct	- 50.233	- 0.988	FCRA	-13.75
						FATA	-13.43
	NONM	+ 10				FPER	-13.57
	NOSM	+ 10				FVEH	-13.62
						FDRU	-11.51
Food and Beverage	REPC	- 10	Direct	0.140	- 0.373	FCRA	- 5.18
						FATA	- 5.06
	BAPC	- 10				FPER	- 5.11
	CAPC	- 10				FVEH	- 5.13
						FDRU	- 4.34
Food and Beverage	REPC	- 10	Indirect	0.002 × 12.073	- 0.064	FCRA	- 0.89
						FATA	- 0.87
	BAPC	- 10				FPER	- 0.88
	CAPC	- 10				FVEH	- 0.89
						FDRU	- 0.75
Spatial Variation in Wealth	GIMI	- 10	Indirect	0.824 × 12.073	- 0.134	FCRA	- 1.87
						FATA	- 1.82
	GICO	- 10				FPER	- 1.84
	INPC	- 10				FVEH	- 1.85
						FDRU	- 1.56
Spatial Variation in Employment	GIJW	- 10	Indirect	0.207 × 12.073	- 0.163	FCRA	- 2.27
	GIJH	- 10				FATA	- 2.22
	GIWP	- 10				FPER	- 2.24
	POJP	- 10				FVEH	- 2.25
	EMJR	- 10				FDRU	- 1.90
	EMPC	- 10					
Income per Capita	INPC	- 10	Indirect	0.00001 × 12.073	- 0.330	FCRA	- 4.60
						FATA	- 4.49
						FPER	- 4.54
						FVEH	- 4.55
						FDRU	- 3.85
Average Household Size	AHHS	- 10	Indirect	0.046 × 12.073	- 0.140	FCRA	- 1.95
						FATA	- 1.90
						FPER	- 1.92
						FVEH	- 1.93
						FDRU	- 1.63
Urban Density	COSM	+ 10	Direct	- 0.002	- 0.293	FCRA	-4.08
	PRSM	+ 10				FATA	-3.98
	FMSM	+ 10				FPER	-4.02
	NMSM	+ 10				FVEH	-4.04
						FDRU	-3.41
Urban Density	COSM	+ 10	Indirect	0.00005 × 12.073	- 0.088	FCRA	- 1.23
	PRSM	+ 10				FATA	- 1.20
	FMSM	+ 10				FPER	- 1.21
	NMSM	+ 10				FVEH	- 1.22
						FDRU	- 1.03
Day & Night-Time Population Density	COPRSM	- 10	Direct	0.001	- 0.434	FCRA	- 6.05
						FATA	- 5.91
						FPER	- 5.97
						FVEH	- 5.99
						FDRU	- 5.06
	COPRSM	- 10	Indirect	0.0001 × 12.073	- 0.524	FCRA	- 7.30

Day & Night-Time Population Density						FATA	- 7.13
						FPER	- 7.20
						FVEH	- 7.23
						FDRU	- 6.11
In-Commuting Flow per Workers	COFW	- 10	Direct	0.122	- 0.067	FCRA	- 0.94
						FATA	- 0.91
						FPER	- 0.92
						FVEH	- 0.93
						FDRU	- 0.78
Education	EDUC	+ 10	Direct	- 1.954	- 2.569	FCRA	-35.76
						FATA	-34.92
						FPER	-35.27
						FVEH	-35.40
						FDRU	-29.93
Presence of Heavy Vehicles	HEVE	- 10	Direct	0.272	- 0.216	FCRA	- 3.01
						FATA	- 2.94
						FPER	- 2.97
						FVEH	- 2.98
						FDRU	- 2.52

TABLE A.6: Complete sensitivity analysis – macro-level urban characteristics and pedestrian safety

Independent Variable (Latent/Observed)	Change in Observed Independent Variables (%)		Effect Type	Coefficient (Unstandardized)	Associate Change in Latent Dependent Variable	Associated Change in Observed Dependent Variables (%)	
	Variable	Change				Variable	Effect
Food and Beverage	REPC	- 10	Direct	0.069	- 0.184	FPED	- 7.23
	BAPC	- 10					
	CAPC	- 10					
Food and Beverage	REPC	- 10	Indirect	0.002 × 9.031	- 0.048	FPED	- 1.89
	BAPC	- 10					
	CAPC	- 10					
Spatial Variation in Wealth	GIMI	- 10	Indirect	0.824 × 9.031	- 0.100	FPED	- 3.95
	GICO	- 10					
	INPC	- 10					
Spatial Variation in Employment	GIJW	- 10	Indirect	0.207 × 9.031	- 0.122	FPED	- 4.81
	GIJH	- 10					
	GIWP	- 10					
	POJP	- 10					
	EMJR	- 10					
	EMPC	- 10					
Income per Capita	INPC	- 10	Indirect	0.000005 × 9.031	- 0.124	FPED	- 4.87
Average Household Size	AHHS	- 10	Indirect	0.046 × 9.031	- 0.104	FPED	- 4.12
Urban Density	COSM	+ 10	Direct	- 0.002	- 0.293	FPED	- 11.54
	PRSM	+ 10					
	FMSM	+ 10					
	NMSM	+ 10					
Urban Density	COSM	+ 10	Indirect	- 0.0001 × 9.031	- 0.132	FPED	- 5.21
	PRSM	+ 10					
	FMSM	+ 10					
	NMSM	+ 10					
Day & Night-Time Population Density	COPRSM	- 10	Direct	0.001	- 0.435	FPED	- 17.11
Day & Night-Time Population Density	COPRSM	- 10	Indirect	0.00005 × 9.031	- 0.196	FPED	- 7.73
Education	EDUC	+ 10	Direct	- 0.815	- 1.072	FPED	- 42.18