THE EFFECTS OF TRAVEL TIME DELAY ON VEHICLE MILES TRAVELED AND TRAVEL MODE CHOICE BEHAVIOR: AN EMPIRICAL ANALYSIS OF THE SEATTLE METROPOLITAN AREA

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10 29, 2018

Dedication

To

Equity for All

Abstract

THE EFFECTS OF TRAVEL TIME DELAY ON VEHICLE MILES TRAVELED AND TRAVEL MODE CHOICE BEHAVIOR: AN EMPIRICAL ANALYSIS OF THE SEATTLE METROPOLITAN AREA

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Traffic congestion is a crucial factor for understanding travel behavior. The scientific evidence has shown that traffic congestion affects air quality, public health, and economic development, but empirical studies about the effects of travel time delays on travel behavior are limited. This research aims to address this gap by developing a time-related mobility measure, or “delay score,” and analyzing its impact on VMT and commuters’ mode choices within a comprehensive framework that incorporates the built environment, demographics, and residential preference/self-selection factors. In this framework, VMT per household and travel mode choice were examined using SEM and GSEM techniques, respectively.

This study used travel survey data from the 2015 Puget Sound Regional Council to analyze household daily VMT and commuter mode choice. Using GPS-based travel survey data combined with spatial analysis techniques, secondary data sources were considered in the analysis to examine factors such as VMT, non-motorized travel, and transit use. Built environment variables were measured at both the origins and destinations of trips. The study also incorporated socioeconomic and residential self-

selection variables. Subsequently, factor analysis was used to represent residential self-selection and the land use density dimension of the built environment.

The findings indicate that higher travel time delay is associated with lower VMT per household, as doubling delay is associated with a 20 percent decrease in household VMT. The findings provide support for policies and regulations aiming to increase density and mixed-use development, reduce road capacity, and improve walkability and access to transit. Increasing the cost of driving relative to other modes is one strategy supported by smart growth policies to reduce VMT and encourage taking public transit or choosing non-motorized modes of travel. The findings suggest that access to free parking at workplaces encourages workers to drive alone, whereas providing free transit passes encourages them to take transit. Additionally, the results indicate that vehicle ownership—as a mid-term indicator—is more related to socioeconomic factors, whereas daily VMT—as a short-term indicator—is more related to built environment factors and residential self-selection.

Future research should examine the effects of traffic congestion longitudinally and attempt to analyze disaggregated data at the national level to further our understanding of traffic congestion and its impacts on travel behavior.

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Chapter 1

Introduction

Travel behavior is a broad subject that can be examined from multiple perspectives. Over the last several decades, numerous studies have examined the determinants of travel behavior and influential factors, addressing built environment attributes, urban form, residential self-selection, and travelers' socioeconomic characteristics (Bento, Cropper, Mobarak, & Vinha, 2005; Bhat & Guo, 2007; Cervero & Kockelman, 1997; Cervero & Murakami, 2010; Ewing, Hamidi, Gallivan, Nelson, & Grace, 2013; Sarzynski, Wolman, Galster, & Hanson, 2006). Researchers who analyzed the built environment have summarized its relationship to travel behavior through a series of "D" factors: Density, Diversity, Design, Destinations, Destination Accessibility, Distance to Transit, Development Scale, and Demographics (Cervero & Kockelman, 1997; Ewing & Cervero, 2010, 2001). In addition to the built environment, other research has focused on travelers' socioeconomic characteristics, with results indicating that gender, race, income, and age affect travel behavior (Bagley & Mokhtarian, 2002; Blumen, 1994; Hecht, 1974; Kitamura, Mokhtarian, & Laidet, 1997; Manaugh, Miranda-Moreno, & El-Geneidy, 2010; Mauch & Taylor, 1997; Trowbridge & McDonald, 2008; Zax, 1990).

Travel behavior comprises several elements. Studies of travel behavior typically focus on person miles traveled (PMT), vehicle miles traveled (VMT), mode split, route choice, and trip frequency (Boarnet & Crane, 2001; Ewing & Cervero, 2010a; Kockelman, 1997). Due to the broad context of travel behavior, previous studies have each analyzed only a subset of travel behavior elements. A review of these studies indicates that built environmental factors such as land use diversity, density, and urban design influence travel behavior outcomes such as travel mode choice, vehicle trips (VT), and VMT (Handy, Lee, Maiss, Walters, & Parker, 2012). Each element of travel behavior has a different relationship with socioeconomic and built environment factors. For example, according to Ewing and Cervero (2010), VMT depends on factors such as built environment, trip frequencies, trip lengths, and individuals' travel preferences (Ewing & Cervero, 2010). A study by Diao and Ferreira Jr. (2014, p. 3004) found that VMT is more strongly correlated with built environment factors such as accessibility to work and non-work destinations, transit accessibility, and connectivity than with demographic factors. Likewise, according to Handy (2005, p. 21), "…characteristics of the built environment are significant predictors of VMT, which is the outcome of the combination of trip lengths, trip frequencies, and mode split." However, Ewing and Cervero (2001), in their comprehensive synthesis, discussed socioeconomic characteristics and the built environment separately. Their results can be summarized as follows:

- The socioeconomic characteristics of travelers are the primary factors that affect trip frequency.
- The built environment characteristics of the neighborhood is the primary factor influencing trip length and VMT.
- Both socioeconomic characteristics of travelers and the characteristics of the built environment affect mode choice, though socioeconomic characteristics are arguably the more important factor.

Other elements of travel behavior include mode of travel and automobile ownership, which are dependent on long-term decisions such as residential location. To examine these elements, Lerman (1976) developed a joint choice model that includes factors such as location, housing, automobile ownership, and mode to work. This study noted that household location, as a long-run decision, strongly influences choices such as auto ownership and mode to work. Considering car ownership and mode choice, Næss (2006) considered the important role of income and home locations. By analyzing data in the

Copenhagen Metropolitan Area, this study found that areas with high car ownership are mostly located in the suburbs, where higher income levels are also found.

Another key but understudied factor that may impact travel behavior—especially VMT and mode choice—is traffic congestion. While the socioeconomic characteristics of commuters and built environment factors influence individuals' mobility patterns, the reliability of traffic conditions affects individuals' travel behaviors, including their daily VMT, trip frequencies, mode choices, and route choices. According to Ben-Akiva and Lerman (1985), traffic congestion is an impedance that increases travel times and travel costs. Due to the negative impacts of traffic congestion, commuters might change their travel behaviors to avoid traffic congestion; for instance, commuters within congested regions might change their departure times—by choosing off-peak hours for their daily trips—or switch to public transit for their daily commutes.

Traffic congestion plays an important role in residents' access to jobs and affects their quality of life. Traffic congestion can be considered an impedance for job accessibility, as it increases travel times and travel costs. Furthermore, understanding the effects of traffic congestion on travel behavior is critical for travel demand models and highway improvements studies. Nevertheless, there is a lack of strong evidence regarding the influence of traffic congestion on travel behavior.

During the last decade, extensive efforts have been made to measure traffic congestion while others have explored the relationship between the built environment and travel behavior (Boarnet, Kim, & Parkany, 1998; Chatman, 2003; Pratt, 2013; Saka, 2009). However, these efforts have involved little overlap; as such, these studies have not clearly presented how traffic congestion influences commuter travel patterns such as VMT, number of trips per day, and mode choice. According to Ewing et al. (2014, p. 3094), congestion is a factor that can affect travel behavior, though this relationship has not been adequately analyzed in previous studies, primarily because measuring traffic congestion requires extensive data with detailed information about the transportation network, road capacity, and traffic volumes. However, recent technological advances in GPS and cellphone data collection have provided new data sources for transportation agencies to measure traffic congestion based on speed and travel time.

Another limitation of travel behavior studies is related to data aggregation. According to Cervero and Murakami (2010, p. 403), data aggregation by metro area can lead to aggregation biases and inconsistent conclusions. Likewise, Ben-Akiva and Bierlaire (2003) noted that the analysis of travel behavior is typically disaggregated analysis (p.5). As a result, analyzing the effect of traffic congestion on travel behavior requires detailed information at small geographic levels. However, the only widely used measure of congestion is developed by Texas A&M Transportation Institute (Urban Mobility Report) at the urbanized area level; a valid and reliable measure of congestion at a smaller scale has not been developed. The present research benefits from using travel time estimates extracted from the Google Maps Distance Matrix Application Programming Interface (API). In this approach, travel time delay (i.e., delay score) is calculated using peak and off-peak travel times. In addition to the disaggregated travel time data, a travel behavior study requires disaggregated household survey data that presents individuals’ travel patterns within urban areas or neighborhoods. To overcome data aggregation biases, the Puget Sound Regional Council (PSRC) is used in the present study to analyze the travel patterns and the socioeconomic characteristics of individual commuters within the Seattle metro area. The PSRC household survey was completed in 2015 and includes the geocoded home, work, and trip locations of 2,442 households and 18,712 trips. Using these disaggregated data, this study investigates the effects of congestion on VMT per household individuals' travel choice behaviors.

Research Objectives

The primary focus of this research is to examine time-related mobility measures and the effects of travel time reliability on vehicles miles traveled (VMT) and commuter mode choice. Time-related mobility measures are easier to understand and provide a more accurate indicator of congestion than network-based measures such as the volume-over-capacity ratio (VOC) or level of service (LOS) (Schrank, Eisele, & Lomax, 2005). However, these time-mobility measures have not always been used because of data limitations. This research presents the process of using GIS and the Google Maps Distance Matrix API to quantify travel time reliability and suggests a process to implement travel time data for travel behavior studies.

Considering congestion, built environment variables, and demographic factors, this research examined different aspects of individuals' travel behaviors. For example, this study examined the effects of local congestion on household daily VMT and estimated the likelihood of carpooling, walking, biking, or taking public transit to commute to work for commuters with higher travel time delays between their home and workplace. For this purpose, this study first developed time-related mobility measures and investigated their impact on household daily VMT within the Seattle Metropolitan Area using structural equation modeling (SEM). Second, this research investigated the influence of traffic congestion on mode choice by using generalized structural equation modeling (GSEM).

In addition to the traffic congestion factor, built environment factors, socioeconomic variables, and residential self-selection factors are considered in both VMT and mode choice models. According to Cervero (2002), many past studies have investigated the effects of densities, walkability, and other built-environment factors on modes of travel; however, these studies “failed to account for the simultaneous influences of factors like travel times and motoring prices” (p.266). The present study examined the interactions between travel behavior and a variety of built environment and demographic factors while focusing on the potential influence of traffic congestion.

With a focus on quantifying traffic congestion and analyzing VMT and mode of travel, the main questions examined in this research are summarized as follows:

- What is an improved methodology for measuring traffic congestion?
- How does household VMT associate with traffic congestion near home locations?
- How does commuting mode choice relate to travel time delay between the origin and destination of trips?
- How does the built environment affect household VMT and commuting mode choice?
- How does residential preference affect household VMT and commuting mode choice?

Driven by these research questions, this study tested the following hypotheses:

- Higher traffic congestion near home locations suppresses household daily VMT.
- Travelers who experience higher travel time delays when driving (1) prefer transit or non-motorized transport as their mode of travel and (2) avoid driving alone and prefer sharing their ride with others.
- Residential preferences based on access to transit or neighborhood walkability mitigate household VMT and increase the likelihood of non-motorized modes of travel.
- Residential preferences based on access to highways increase household daily VMT and decrease the likelihood of non-motorized modes of travel.

Testing these hypotheses can provide important information for improving travel demand models, especially activity-based models. Also, understanding travelers’ reactions to traffic congestion can provide modeling estimates to aid future studies of land use planning, toll roads studies, and HOV/managed lane projects.

Empirical Analysis

Data

This study incorporated travel survey data from the Puget Sound Regional Council (PSRC) completed in April and June of 2015. The sample comprises 2,442 households in the Seattle Metropolitan area with geocoded home, workplace, and all other trip-end locations. Several factors such as population density, road density, and transit accessibility were extracted from land use and built environment data using a geographic information system (GIS). In addition to socioeconomic and built environment data, the Google Maps Distance Matrix Service API was used to calculate travel time delays and quantify a delay score.

Statistical Approach

This research adopted a comprehensive framework for analyzing travel behavior by including time-related mobility measures and self-selection factors in addition to the built environment and socioeconomic variables. It involved using an improved time-related travel delay measure and implementing SEM, a statistical technique also known as correlation structure analysis and covariance structure analysis. SEM is a powerful statistical method for considering the direct and indirect effects of observed variables and calculating the covariance or correlation between two variables as functions of the parameters of the model. One advantage of SEM for the present study is that multiple statistical tools such as equations, path diagrams, and matrices can be integrated into a single framework that is appropriate for analyzing built environment factors, which are generally correlated with one another.

The SEM technique was used to investigate the association between household daily VMT and factors such as density, demographics, and residential self-selection. As VMT—the outcome variable—is a continuous factor, it meets the requirements for analysis via SEM. However, the mode choice analysis—with discrete outcomes—cannot be modeled by SEM. To model discrete outcomes, GSEM was used to estimate the effect of various built environment characteristics on mode choice, implementing both multinomial logit (MNL) and structural equation (SE) models. This approach allows for simultaneous analysis of all the variables in a model that considers a system of related regression equations.

Applications of Research

This study evaluated two major outcomes of travel behavior—VMT and mode choice—by analyzing the influence of traffic congestion, the built environment, and socioeconomic characteristic on commuters' travel behavior. By including time-related mobility measures, particularly travel time delay, the effects of traffic congestion on VMT and mode choice can be evaluated and implemented in travel demand models. Using the Google Maps Distance Matrix Service, this research enhances our understanding of household daily VMT as well as individual travel choice behaviors based on traffic congestion between home and work locations. Ultimately, this research provides evidence supporting the hypothesis that traffic congestion affects particular facets of travel behavior such as VMT and mode choice.

Thesis Organization

The primary focuses of this research are to explore the impact of traffic congestion on VMT and mode choice and describe how to properly quantify congestion. To achieve these goals, the thesis is divided into six chapters. Chapter 1, the current chapter, briefly introduced the objectives, hypotheses, and applications of this research.

Chapter 2 provides background regarding theories relevant to travel behavior by discussing transport economics theories, social theories, the theory of planned behavior, utility maximization theory, and the rational-choice paradigm. The second part of this chapter discusses behavioral models and the limitation of activity-based models. Ultimately, this chapter summarizes the theoretical framework of the present research.

Chapter 3 provides a literature review, addressing empirical results on how the built environment and socioeconomics affect travel demand. This chapter begins with a review of related studies investigating the interaction between land use and transportation systems. Then, the relationships between socioeconomic characteristics, residential self-selection, and travel behavior are explored. In general, this chapter addresses the question of how to quantify traffic congestion and examines the basic requirements for properly measuring traffic congestion.

Chapter 4 focuses on this study’s methodology and the process of data integration. This chapter describes the data that were collected, extracted, and integrated in this research. The data integration section presents a summary of socioeconomic and built environment data, traffic congestion, and the process of cleaning and extracting household travel survey data. Then, this chapter examines how descriptive, exploratory, and statistical methods, such as SEM and GSEM, were applied to analyze the relationships between the explanatory variables. Additionally, this chapter introduces the selected method for quantifying traffic congestion and describes how to calculate a delay score using the Google Maps Distance Matrix API.

Chapter 5 begins by describing the results of the VMT model that was developed via SEM. Then, this chapter provides a summary of the criteria for model validation and describes the ways in which the analyzed variables vary. The second part of Chapter 5 describes the results of the mode choice model using MNL estimates via GSEM. This chapter also describes the process of validating the mode choice model and explains the coefficient estimates in terms of the likelihood of selecting each travel mode.

Chapter 6 summarizes the major results of this study and discusses the limitations of the present research, its contribution to the literature, avenues for future research, and implications for policies and regulations. This chapter concludes with a discussion of what to do about traffic congestion and how policies can be implemented to reduce VMT and encourage non-motorized mode of travel.

Chapter 2

Theories Relevant to Travel Behavior

In scientific research, the term “theory” refers to a set of assumptions, general laws, or accepted facts that attempt to provide predictions and plausible explanations of causal relationships between a group of observed events. Travel behavior has been examined through several theoretical frameworks such as social theories, urban economics, and behavioral science. This chapter begins with theories of transport geography and urban economics such as central place theory (Christaller, 1966), bid rent theory, and the monocentric model of urban form developed by Alonso (1964). This chapter then reviews travel behavior based on social theories such as utility-maximizing theory, the theory of planned behavior, social-cognitive theory, and critical realism. Finally, this chapter provides more details regarding behavioral models, such as the activity-based approach, and their limitations.

Transport Economics Theories

Debate over central places, urban structure, and market interactions between firms and households can be traced at least as far back as Hotelling’s Law. In 1929, Hotelling argued that businesses with higher profits are located close to competitors in the center of a region (i.e., central place). According to Hotelling’s Law, there is an “undue tendency for competitors to imitate each other in quality of goods, in location, and in other essential ways” (Hotelling, 1929: 41).

Hotelling’s model has been improved by the inclusion of price competition and a bid-rent framework. Alonso (1964) presented the concept of bid-rent theory and the influence of distance to central places on land rent and transportation costs. The bid-rent framework implies that central places with a higher density of activities are expensive, and high-income groups or firms will be located in these areas. Based on the bid-rent framework, individuals who can choose their preferred residential location must have enough income to outbid competitors. This mechanism causes higher land prices at central places, with building heights in central locations increasing exponentially.

The bid-rent framework utilizes a function associated with multiple factors. This complex function can be examined by variables such as income, density, and distance to facilities, among others. Accessibility between activities and residential locations provides the key connection between origins and destinations. Accessibility to central places is the main reason for agents to compete for land. According to O'Sullivan (2009), the willingness to pay for land depends on its accessibility within urban areas because of reduced travel cost.

Firms from various sectors and households are allocated to different locations based on land prices and willingness to pay. That is, manufacturing firms are attracted toward highways that connect the city to consumers, whereas households are attracted to areas near employment with lower commuting costs. In response to high land prices, tall buildings are oriented toward central places and land is allocated to the highest bidder. The bid-rent theory explains that firms and households have limited resources and they compete with one another to obtain the optimal location that minimizes their respective costs. Furthermore, households consider the exchange between land rent and transportation costs when choosing residential locations, whereas firms attempt to minimize the cost of production by reducing their transportation costs in the production process (Giuliano, 1989). Based on this framework, available land is assigned to the highest bidder who gains the most benefits from that location. This competition among households and firms shapes urban structure and influences commuting patterns.

Choosing workplace and residential locations is a fundamental component of the bid-rent theory. The commuting of workers between activity centers is associated with supply and demand for labor at each location, and it is associated with accessibility to, the proximity of, and the density of activities. Also, travel time causes costs for each commuter. This relationship between workplace and residential locations originates from the bid-rent framework of the Alonso-Mills-Muth model. According to this bid-rent model, increasing distance from central places will raise trip costs as workers need to spend extra time commuting instead of working or being with their family. For this reason, all other things being equal, workers typically prefer to minimize their travel time.

Another component of the bid-rent theory is density, which is related to the concept of so-called “agglomeration.” Agglomeration benefits are key to understanding not only why cities exist but the form of urban spatial structures in general. Higher density provides more profit for firms and households, as it reduces distances and trip costs between activities. According to O'Sullivan (2009), economic forces push firms and businesses to be located close to one another in clusters. A higher density of economic activity can be seen in central business districts (CBD) or marketplaces because more producers and more consumers prefer to visit central places due to their proximity and lower transportation costs. According to Maddison et al. (1997), the concept of “distance decay” defines the attractions of central places. The empirical evidence indicates that central places have developed not only to benefit businesses but also to benefit households, since living near central places reduces trip costs and facilitates consumption.

The importance of CBDs and their impact on urban structure is another subject of considerable debate. CBDs have a notable role in traditional urban theory (i.e., the Alonso-Mills-Muth model). However, according to Anas et al. (1998), “edge cities” (i.e., subcenters) have been developing as populations and places of employment shift from central urban areas into suburbs. The term of “edge cities” was introduced and popularized by the book “Edge City,” in which Garreau (1991) describes edge cities as areas with diverse employment centers and amenities that have developed near highway intersections, freeways, major airports, and intermodal transport facilities to easily connect them to CBDs. Although a large portion of the population and businesses moved to the edge cities, as Glaeser et al. (1992) stated, central places are still vital as many firms and businesses choose to locate their corporate headquarters in CBDs and their production facilities outside of cities. CBDs are still dominant and exhibit the highest population and employment densities with higher land prices, even after the rapid suburbanization process. The accessibility between CBDs and subcenters highlights that CBDs and subcenters are strongly connected, with subcenters serving a complementary role rather than competing with CBDs.

The relationships between travel behavior, urban form, urban structure, and residential/employment locations have been the main subject of several urban economic studies (Anas, Arnott, & Small, 1998; R. Dubin, 1991; Giuliano & Narayan, 2003; Giuliano & Small, 1993; Gordon, Kumar, & Richardson, 1989; Gordon, Richardson, & Jun, 1991; Hamilton & Röell, 1982; Horner, 2002; Small & Song, 1992; Thaler, 2017; Waddell, 1993; White, 1986, 1988; M. Zhang, 2004). However, in addition to urban structure and land use patterns, the characteristics of travelers influence travel behavior. The next section describes the connection between human behavior and the environment through a review of relevant social theories.

Social Theories

Building a theory of general human behavior is a unique difficulty, as there are problems associated with assuming rational actors, identifying rational criteria, and determining the “fundamental laws” of psychology (Chadwick-Jones, 1976). Therefore, social theories commonly explore the mechanisms determining—and the factors influencing—specific categories of behavior, including travel behavior. Nevertheless, several foundational theories of human behavior were developed throughout the 20th century, which continue to be debated and refined today.

The general concepts of human motivation, self-adjustment, self-actualization, and social adjustment were introduced by philosophers such as Abraham Maslow and Carl Rogers (Maslow, 1943; Rogers, 1959). Considering the self and the mind in terms of a social process, George Herbert Mead presented a detailed explanation of human behavior and its interaction with the environment (Ganter & Yeakel, 1980; Mead, 1934). Trait Theory is another example of theorizing that investigates the internal determinants of behavior (Allport, 1966; Cattell, 1966). These ideas presented that there are various ways of perceiving the world based on experience and social environment, and these influence human behavior (Adams, 1973). According to Bandura (1986), the concept that people can change their own motivation and actions by exercising self-influence is presented by theorists who view humans as possessing capabilities for self-direction.

While classical sociologists focused on individuals and their relationship with society and understanding social realities, modern social theories were developed based on the agency-structure framework. According to Krasner (1969) , human behavior can be influenced by any situation that includes government, education, religion, or other social and cultural structures in their interaction. The connection between structure and agents is one of the most debated topics in social theory. Talcott Parsons (1977 as cited in Mouzelis, 2008), who is considered the father of modern sociological theory, places emphasis on systems and structures that can be assessed by two basic axes: the micro-macro and action-system dimensions (Mouzelis, 2008; Parsons, 1977). The main contribution of Parsons towards the construction of a structural functionalism is linking the macroscopic and microscopic levels of analysis. His conceptualization of social systems and subsystems can be applied to empirical studies addressing social behaviors at the macroscopic, mesoscopic, and microscopic levels.

On the other hand, Anthony Giddens, who developed the concept of structuration suggests perspectives on human behavior based on a synthesis of structure and agency effects known as the “duality of structure.” (Giddens, 1979). According to Mouzelis (2008, p. 35), Giddens rejected the actor/social-structure dualism found in the conventional social sciences—i.e., the idea of actors being constrained by social structures external to them. In the process of structuration, actors and structures are inextricably connected and there is not an externality or distance between actors and structures. In contrast to Gidden’s Structuration Theory, social theories such as the Theory of Action (Alexander, 1982), Social Cognitive Theory (Bandura, 1986), Critical Realism (Bhaskar, 1989) , and the Theory of Planned Behavior (Ajzen, 1991) have examined the effects of human characteristics on behavior, addressing cultural, social, and personality factors. The Theory of Action, developed by Alexander, presents human action as the outcome of three systems: the cultural, social, and personality systems. According to Alexander (1982), the cultural and personality systems are internal to the actor while the social system/environment is external. Alexander (1998) argues that action is formulated by the cultural environment and motivated by ‘personalities.’

Social Cognitive Theory, introduced by Bandura (1986), describes human behavior via a model of triadic reciprocal relationships in which behavioral, environmental, cognitive, and other personal factors all serve as cooperating determinants of each other. In this framework of reciprocal determinism, which is illustrated schematically in Figure 1, human behavior can be explained based on “reciprocal relationships” between the individual’s characteristics, the individual’s behavior, and the environment. (Bandura 1986; Handy 2005). In this triadic reciprocal determinism, the term “reciprocal” denotes the mutual action between causal factors (Bandura, 1986, p. 23). In other words, “this concept does not mean perfect symmetry in the strength of the influences between each pair of components, nor does it mean that the interactions happen simultaneously” (Handy 2005, p. 14).

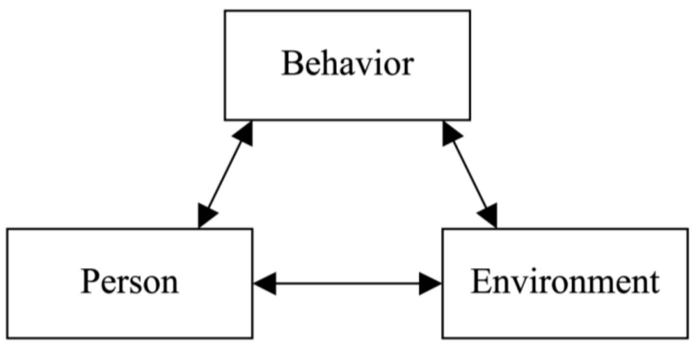

Figure 1. Reciprocal Determinism

Source: Handy, 2005 (adapted from Bandura, 1986)

Critical Realism is another fundamental framework that presents the relationship between structure and actors. In contrast to Social Cognitive Theory, Critical Realism argues in favor of simultaneous interactions between structures and agents. Critical Realism was inspired by Marx’s view of science and introduced by the philosopher Roy Bhaskar (Bhaskar, 1989). It provides a framework that explains human action (including travel behavior) and its association with structural conditions such as land use, transport systems, and patterns of development. The theory of Critical Realism also contrasts

Structuration Theory in terms of the connection between structure and agent. Gidden's (1984) Structuration Theory claimed that "agency and structure are mutually constitutive and cannot be united." (Næss, 2006, p.12). In contrast to Giddens theory, Critical Realism claims that "both structures and agents have particular properties and causal powers" (Næss, 2006, p.14).

According to Næss (2006), the built environment around us is socially constructed. The "construct" includes both physical aspects and immaterial structures. The physical aspects of the structures include roads and buildings, whereas the immaterial structures include cultural traditions, economic conditions, and dominant belief systems. In terms of Critical Realism, the structures are being simultaneously modified and transformed by human actions. Such transformations most often proceed slowly and gradually, but some happen rapidly (Næss, 2006, p.13).

Critical Realism is based on the assumption that both agents and structures have specific characteristics and causal powers (Archer, 2000; Danermark, Ekstrom, & Jakobsen, 2001; Næss, 2006; Sayer, 1992). In this framework, causality is not restricted to monocausal relationships. Instead, causes are rather considered as "tendencies" that may or may not occur. Therefore, the situation of multiple causes should be considered when explaining behaviors such as the travel behavior of commuters. Sayer (1992, p.117) presented causal powers as "structure" utilizing the Critical Realism framework; as shown in Figure 2, the structure (causal powers) has the potential to impact events (observable phenomena) through several mechanisms (Næss, 2006).

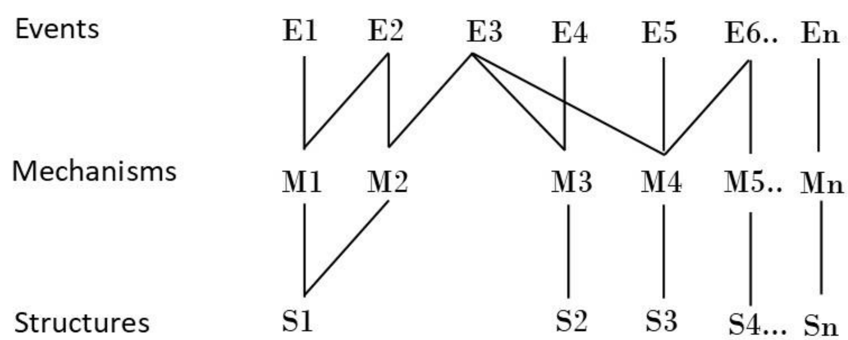

Figure 2. Structures, Mechanisms, and Events in Critical Realism

Source: Næss, 2006 (based on Sayer, 1992)

Many researchers have emphasized the importance of a necessary or sufficient condition when analyzing the term “cause” in relation to the causes of travel behavior. As explained by the Critical Realism framework, there are various contributory factors that influence individual travel behavior. However, it is important to note that certain conditions are required to activate the mechanism. Although environmental structure affects travel behavior, sometimes those factors are not sufficient to influence some aspects of travel behavior. In other words, the combination of mechanisms in particular conditions is required to cause an event.

Addressing “causes and conditions,” Mackie (1965, as cited in Næss, 2006) introduced the concept of an “INUS condition” that is, “Insufficient but Necessary parts of a condition which is itself Unnecessary but Sufficient” (Næss, 2006, p. 14) According to Næss (2006), the effects of the built environment could be examined as INUS conditions. The condition of the built environment cannot be attributed the status of a sufficient condition for certain travel behaviors, such as walking or taking public transit. Accordingly, several other circumstances will influence this behavior, such as the wishes and preferences of the traveler, health status, and access to means of transport. Higher density may be necessary for creating a walkable place, but density itself is not sufficient to determine the commuter's mode choice behavior. A resident who lives downtown may choose to make a short trip by walking in the morning because this action, according to the person's beliefs, is the most reliable means to reach the workplace in time. Based on the concept of INUS condition, the commuter's mode choice is the outcome or result of various contributory causes. Factors such as the short distance between home and the workplace are a necessary and sufficient condition for commuters to walk from home to work in order to reach their destination on time.

The Theory of Planned Behavior

Another framework that can be used to understand travel behavior is the Theory of Planned Behavior (TPB), which is an extension of the Theory of Reasoned Action (TRA) developed by Ajzen and Fishbein in 1975. According to Azjen (1991), "Attitudes toward the behavior, subjective norms with respect to the behavior, and perceived control over the behavior are usually found to predict behavioral intentions with a high degree of accuracy. In turn, these intentions, in combination with perceived behavioral control, can account for a considerable proportion of variance in behavior." (p. 206). Azjen's (1991, as cited in Karash et al., 2008) framework includes these components of human behavior:

- Attitude Toward the Behavior: An individual's own evaluation of an action, such as driving alone from home to work or taking public transit for a day.
- Subjective Norm: An individual's perception of what others will think if he/she takes an action (e.g., what colleagues will think if he/she takes public transit).
- Perceived Behavioral Control or Self-Confidence: An individual's assessment of his/her ability to take an action, such as taking public transit (Karash et al., 2008, p. 6).

As shown in Figure 3, TPB argues that intentions, attitudes (beliefs about a behavior), and subjective norms (beliefs about others' attitudes toward a behavior) determine behavior (Ajzen, 1991, 2011; Ajzen, Heilbroner, Fishbein, & Thurow, 1980; Fishbein & Ajzen, 1975) In this framework, Azjen distinguishes between behavior beliefs, normative beliefs, and control beliefs, which impact attitudes, subjective norms, and perceived behavioral control, respectively (Handy, 2005). Based on the theory of planned behavior, each person has different reactions and thresholds to response based on these three elements. Additionally, attitude, subjective norm, and self-confidence all contribute to an individual's intent to carry out a behavior. (Karash et al., 2008).

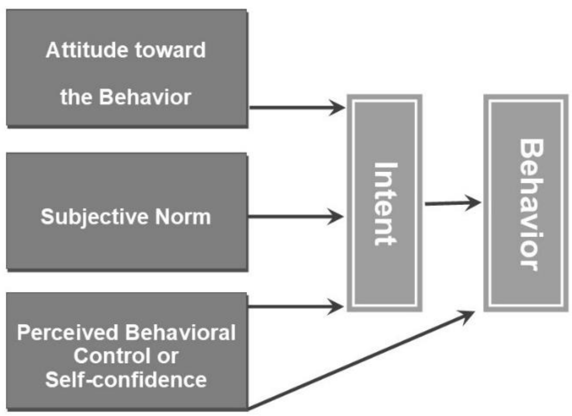

Figure 3. Theory of Planned Behavior

Source: Karash et al., 2008

The Extended Theory of Planned Behavior considers two additional components, as illustrated in Figure 4. According to Karash et al. (2008), life cycle has a great influence on an individual's attitudes about choices. The life cycle includes various factors addressing age, gender, marriage, and other socioeconomic/demographic characteristics. For example, young teens, as compared to older adults, may be more influenced by others' mindsets.

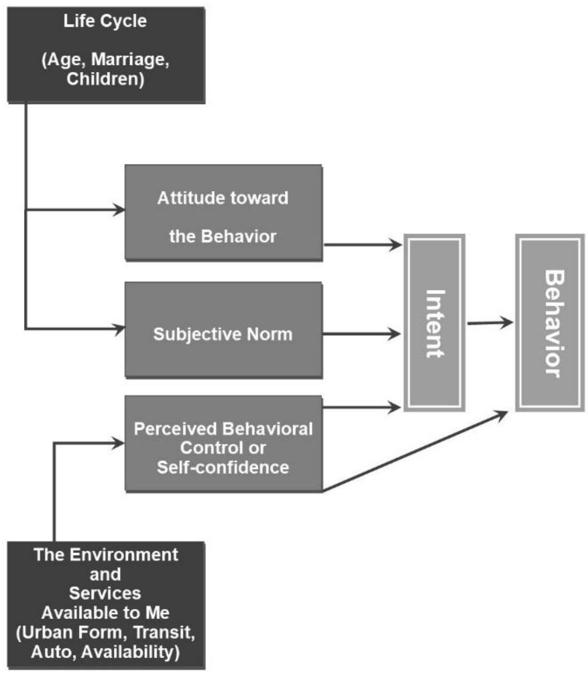

Figure 4. The Extended Theory of Planned Behavior

Source: Karash et al., 2008

According to Stopher et al. (1981), there are two main constraints that can limit one's choice set: externally imposed and self-imposed constraints. Externally imposed constraints are linked to the characteristics of the alternative and other external factors. The self-imposed constraints are associated with life cycle and personal attitudes toward the behavior. According to Stopher et al. (1981, p. 198) , "…a distinction should be made between externally imposed and self-imposed constraints. Car availability may be externally imposed but in some cases is a self-imposed constraint that to some extent may rest on a reversible decision". From a psychological theoretical basis, TPB should be examined to identify these constraints. For example, in a car ownership choice set model, constraints imposed by each individual's and household's circumstances limit the commuter's ability to own a car. For car ownership and mode choice, the main constraint can be defined by income or budget constraints.

The Rational Choice Paradigm

Rational Choice Theory constitutes another important paradigm based on the economic concept of consumers making choices on the basis of maximization or optimization criteria. This idea, in both Marxist and non-Marxist frameworks, presents a useful conceptual framework with an emphasis on agency and the rational behavior of actors (Mouzelis, 2008, p. 19). The concept of "utility-maximizing behavior" originated from economics and psychology and was introduced into travel behavior research by McFadden (1974) in his Nobel prize-winning work. The theory focuses on individual choice behavior and indicates that people will choose the alternative which maximizes their benefits and provides the largest utility. As explained in bid-rent theory, households and firms compete for land, which is ultimately occupied by the highest bidder. The utility-maximization concept is a proper framework to explain how households choose their location and their travel mode, as well as how much a household bids for land in a specific location.

Travel behavior has both continuous and discrete outcomes. Trip frequencies, VMT, and PMT are continuous outcomes that can be examined by well-known methods such as linear regression. On the other hand, travel choice analysis—such as travel mode and route choice—is based on discrete choice modeling through methods such as multinomial logit models.

A key assumption of discrete choice analysis is that each person is going to make a single choice—from a finite set of alternatives—that maximizes his or her benefits. In the choice set, the probability of selecting a specific alternative is based on the utility of this alternative relative to the utilities of all the available alternatives (Van Acker & Witlox, 2007). Each one of these alternatives has its own characteristics such as cost, comfort, travel time, and other factors. Each commuter has a different way of joining these characteristics into a ranking, or “utility function.” The utility function can be defined as a linear function of the choice alternatives’ characteristics and individual socioeconomic characteristics such as age, income, and gender. Commuters have different preferences. One commuter might consider delay travel time but not comfort, and consequently choose to take the bus. Others might consider comfort but not travel time, and they'll choose to take a car. These are called “commuter’s preferences,” and individuals have different preferences which can be expressed by the utility function.

Discrete choice models use data on the characteristics of commuters, attributes of alternatives, and market shares to examine commuters’ preferences over different alternatives. According to Ben-Akiva and Lerman (1985), the discrete choice framework includes four components: decision-maker, alternatives, attributes of alternatives, and decision rule. The decision-maker can be an individual, a household, or a firm, for example. This component also considers the decision-maker’s relevant socioeconomic characteristics, such as age, gender, and income. Alternatives are the options composing the choice set, from which a decision-maker can select one. The third component of discrete choice is the attributes of alternatives such travel time and cost. These factors affect a decision maker’s choice. The last component of discrete choice is the decision rule, or the individual’s willingness to choose one alternative. The decision rule can be modeled based on dominance, satisfaction, and utility function. The utility of any choice depends on the characteristics of the individual and the characteristics of that choice.

Short-term and long-term decisions affect travel behavior. According to Handy (2002), individuals' choices can be classified as long-term choices, mid-term choices, and short-term choices. For example, daily travel behavior, such as travel mode, destination choice, and route choice might depend on long-term decisions such as residential and job location. There are various factors affecting commuters' choices, such as built environment factors and socioeconomic characteristics. Figure 5 presents an example of those choices and other influential factors. Thus, Rational Choice Theory and the concept of utility maximization provide a conceptual framework in which relationships exist between several choices. This framework is based on the assumption that individuals make rational choices among a set of alternatives to maximize their net benefit or personal utility (Ben-Akiva & Lerman, 1985; Cervero, 2002; Domencich & McFadden, 1975; Small & Winston, 1999).

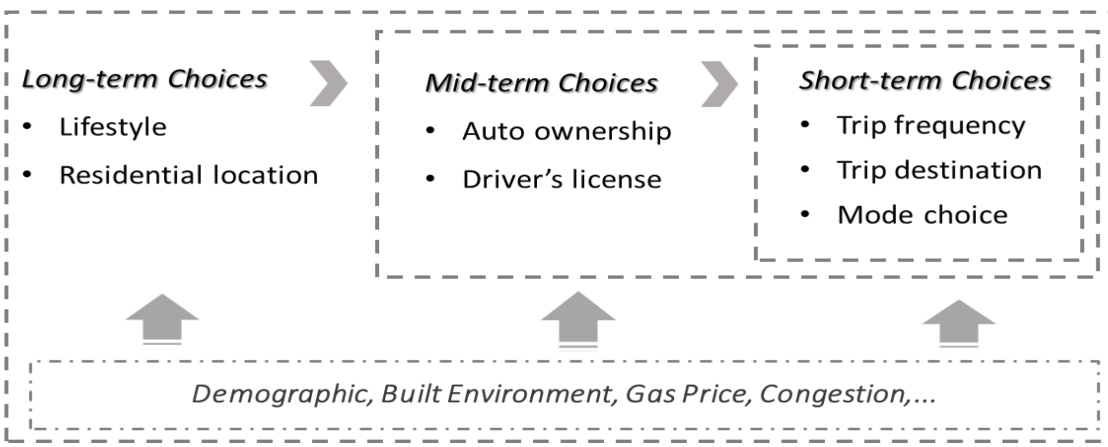

Figure 5. Choice Sets

Source: Adapted from Handy, 2002

Behavioral Models: Activity-Based Approach

Following the theoretical models explained in the previous section, the connections between travel behavior, land use, and the socioeconomic characteristics of commuters have been examined from a variety of perspectives. Since the 1950s, different models have been developed to understand and simulate individual travel behavior. The first generation of travel demand models emerged in the 1950s, commonly referred to as traditional or “four-step” models. Four-step travel demand models are trip-based models developed in the context of insufficient computational capability and aggregated travel survey data (de Dios Ortúzar & Willumsen, 2011; Muro-Rodríguez, Perez-Jiménez, & Gutiérrez-Broncano, 2017; Rasouli & Timmermans, 2014; Stopher et al., 1981).

Traditional four-step models are based on aggregated households grouped into Transportation Analysis Zones (TAZ). In traditional models, trips are generated from TAZs and each trip is independent of every other trip’s generation, distribution, mode choice, and timing. Four-step models are based on person-trips, which do not capture any dependency between members of the same household (Oppenheim, 1995; Stopher et al., 1981).

To overcome the limitation of trip-based models, behavioral models such as activity-based models emerged in the 1970s and have progressively developed along with computing power and the increasing availability of disaggregated travel survey datasets (Rasouli & Timmermans, 2014). In behavioral models, travel is a derived demand that results from the need of people to engage in activities outside the home (Næss, 2006). According to Rasouli and Timmermans (2014), the key concept of activity-based modeling is based on economic location theories (e.g., Central Place Theory) and the profit-maximization behavior of commuters (e.g., Rational Choice Theory).

Activity-based travel models simulate individual mobility based on behavioral decision-making theory. In these models, households are considered in a disaggregated form, individual choices are simulated, and individual activities, trips, and tours are generated and scheduled in different sub-models. In activity-based models, trips are chained and modeled as part of tours, sub-tours, and larger daily activity patterns.

The integration of models and sub-models is a key advantage of activity-based modeling. In four-step models, travel demand is not affected by accessibility or the built environment, whereas built environment factors, accessibility measures, and the starting and ending times of activities are integrated into activity-based models. Also, activity-based models integrate travel throughout the day—considering how decisions are made—and are sensitive to cost, time, demographics, and policies (Rasouli & Timmermans, 2014). The behavioral study of individuals is another advantage of activity-based models, as they allow for greater spatial and temporal details to track individuals' travel behaviors rather than relying on the averages of aggregated zones (Rasouli & Timmermans, 2014).

In an activity-based model, each travel behavior is based on how people make decisions. As Schönfelder and Axhausen (2010) have indicated, in an activity-based model, travel behavior is modeled consistently throughout the process, including trip chaining. Temporal, spatial, and interpersonal restrictions are also considered in activity-based models. Time is a key component in activity-based models, since it allows for travel time and cost to be included in higher level components of the model such as auto ownership and trip generation.

Another advantage of activity-based modeling is their ability to analyze performance measures. Behavioral models can be used to determine sensitivities to policies and conduct more intuitive analyses than traditional models. Activity-based models produce performance measures that are not possible with traditional methods. This makes them better suited than trip-based models to address policies that affect how people make travel decisions. The raw output of activity-based models includes disaggregated trip records, with important identifying attributes such as purpose, start and end times, primary travel mode, location, tour purpose, and primary location. This allows the decision-maker to summarize the system's performance by various dimensions. For example, activity-based models provide travel behavior metrics such as mode share, trips per tour, shopping trip frequencies, and the number of tolls paid.

Other advantages of behavioral models include their capacity for detailed spatial analysis and temporal analysis. Activity-based models can be developed at a highly detailed levels, ranging from parcels and census blocks to households and individuals. This increased spatial detail provides more analytical precision than is possible with traditional models. Regarding temporal analysis, activity-based models can estimate time-of-day intervals of 30 minutes or even 5 minutes, whereas traditional four-step models are estimated based on average peak hours and off-peak hours. In an activity-based model, the time chosen for travel is represented by the complex demands of household members, work, and school schedules.

Limitations of Behavioral Models

Despite their strengths, behavioral models do have limitations and have faced criticism in recent years. The main criticism from social psychologists and micro-sociologists is that *"homo* rationalis" is a fiction. They argue that people do not behave in a perfectly rational way, as the model suggests or simulates (Mouzelis, 2008). According to Muro-Rodríguez (2017), "Most of the models used for travel behavior applications are based on utility theory. This concept presents strong limitations for practical applications, since the complexity of human behavior suggests that the decision rule must include a probabilistic dimension” (p. 2).

One limitation of activity-based models is that they estimate static models to simulate the travel patterns of a typical day. According to Rasouli and Timmermans (2014), activity-based models should become time-dependent as a function of dynamically changing needs, specific events, weather and season (p. 48). Also, attempts to expand the scope of these models to “problems of joint decisions, group (e.g. social networks) decisions, and dynamic choice problems should be applauded” (Rasouli & Timmermans, 2015, p. 26).

Another limitation of activity-based models is related to the route choice algorithm and the lack of integrity between the network assignment algorithm and sub-models such as the time-dependent origin-destination (OD) matrices. Although activity-based models have improved the integrity between sub-models, the integration of demand generation and network assignment needs fundamental improvement to simulate the time-dependent OD matrices (Rasouli & Timmermans, 2014, p. 49).

Another limitation of activity-based modeling is assessing transportation policies. Although activity-based modeling has improved the process of analyzing performance measures, current models are focused on typical performances indicators such as VMT. They need to be extended to other measures such as air quality, emissions, health-related indicators, and quality of life. In addition to policy performance analysis, activity-based models are not intensively integrated with recent advanced technology. According to Rasouli and Timmermans (2014), the linkage between Information and Communication Technology (ICT) and behavioral models is not well developed in current activity-based models. With new technologies, such as smartphone data and mobile computing sources, comprehensive activity-based models of travel demand should be updated by considering activities and travel episodes together.

Another limitation of activity-based models is that current choice models do not properly consider the complexity and nonlinearity of human decision-making. According to Rasouli and Timmermans (2014), current choice models, such as the utilitarian approach, should be improved by using a hybrid choice model or other approaches such as SEM. Decision making under uncertainty is another shortcoming of activity-based models; according to Krishnamurthy and Kockelman (2003), there are many uncertainties with respect to the predictions and accuracy of travel demand models due to model misspecification, imperfect input information, and the innate randomness of events and behaviors. As activity-based models are based on individual decision-making, it is necessary to consider short-term changes in activity-based travel patterns, group decision-making, and family decision-making with a focus on social networks and the dynamic impact of social influences. Modeling intra-household interactions requires complex models such as SEM and more computational time to demonstrate how travel is coordinated among household members.

Finally, behavioral models are not widely adopted by transportation planning agencies for these reasons: First, decision-making under uncertainty with a lack of empirical evidence is the main reason for not adopting behavioral models in planning practices. Second, activity-based models are dependent on the level of detail, quality, and completeness of the data. These data should consider not only individuals' behaviors but also explore institutional constraints, such as opening and closing hours for stores and businesses. Finally, the validation and calibration of behavioral models are impacted by uncertainty since they are based on various choice alternatives and probabilistic forecasts with their own uncertainties and assumptions (Rasouli & Timmermans, 2014).

The utility function is based on “unbounded rationality,” assuming that peoples’ preferences are consistent and that they can reliably select the optimal alternative that maximizes their utility. However, according to Simon (1982), it is not practical to simulate human choices via a utility function. Therefore, Simon introduced “bounded rationality” as a concept opposed to unbounded rationality, highlighting that people make decisions in an uncertain world.

Bounded rationality is typically intended as a warning for interpreting the deterministic outcomes of utility functions, as we cannot predict human behavior by setting up an abstract model. According to Simon (1982), the actual choices people make are different from ideal choices in economics because all alternatives are not known by the decision-maker. Our ability to choose the optimal solution is constrained by the amount of information available, environmental factors, and even physical ability. In other words, consumers are rationally bound with biases and errors due to cognitive limitations.

Simon (1956) referred to “satisficing” instead of “optimizing” and studied how people make a decision when optimization is out of reach in an uncertain world. He believed that people follow simplified guidelines (i.e., heuristics) that can lead to satisfactory solutions, but not necessarily optimal solutions. Moreover, according to Andrew Lo (2017), humans do not maximize and do not optimize; rather, they simply engage in heuristics that are good enough or satisfactory. As Lo (2004, 2017) stated, people do not know when the “optimal” has arrived, and they simply behave through trial and error heuristics that typically make them satisfied.

Considering bounded rationality, it is possible that household circumstances can limit an individual’s ability to respond to congestion. As Rasouli and Timmermans (2015) noted:

…choice behavior in the real world may be guided by principles of bounded rationality as opposed to typically assumed fully rational behavior, based on the principle of utility-maximization. Under such circumstances, conventional rational choice models cannot capture the decision processes. (p. 95)

Subsequently, Rasouli and Timmermans (2015) concluded:

> …trip makers do not recognize each alternative equally. Due to the incomplete information, the consideration of different alternatives on the choice utility might not be equal. In other words, individuals may show an unequal and asymmetrical evaluation about different alternatives in the choice process. (p.59)

Although the utilitarian approach has its limitations, discrete choice theory has provided a practical framework for examining the causal relationship between land use and travel behavior (Handy, 1996). For this reason, utility functions are considered appropriate to implement in travel behavior studies.

Utility Maximization Theory

Travel behavior has been explained by a variety of theories, as presented throughout this chapter. Utility Maximization Theory (Ben-Akiva & Lerman, 1985; Domencich & McFadden, 1975; Train, 1986; Horowitz, 1980; Walker & Ben-Akiva, 2002), which is based on microeconomics theory, is the primary theoretical framework of the present research to explain the effects of traffic congestion on commuter choices. In studying travel behavior, Utility Maximization Theory—utilizing discrete choice analysis—was first introduced by Domencich and McFadden (1975) and was further developed by Ben-Akiva and Lerman (1985) and Train (1986). In this approach, travel behavior can be altered and changed based on the transportation system and its alternatives. Traveling from each location to other destinations can be achieved by various alternatives such as public transit, walking, or driving. Each possible choice provides a certain “utility” or value to the individual, who tries to maximize his or her utility, which includes minimizing travel time for traveling between locations (Handy, 2005, p. 20).

The challenge for transportation planners is to understand the relationship between an individual’s trip-making activity and built environment factors. According to theories of transport geography and transport economics, the demand for moving between activities generates trips (Handy, 2002; Næss, 2006; Stern, Salomon, & Bovy, 2002). As Næss (2006) indicated, trip generation is the need to engage in an activity at a different place, and demand for travel is the result of activities determined by land use patterns. Næss (2006) considers urban structure as a contributory cause of travel behavior within a multi-causal framework based on Critical Realism. As Næss (2006, p. 14) explains, “Causality is not limited to mono-causal relationships and Causes are rather seen as tendencies.” According to Næss (2006), travel behavior is a multi-causal phenomenon with a number of contributory causes. Figure 6 illustrates the multi-causal relationship between transportation behavior, land-use patterns, and individuals’ characteristics.

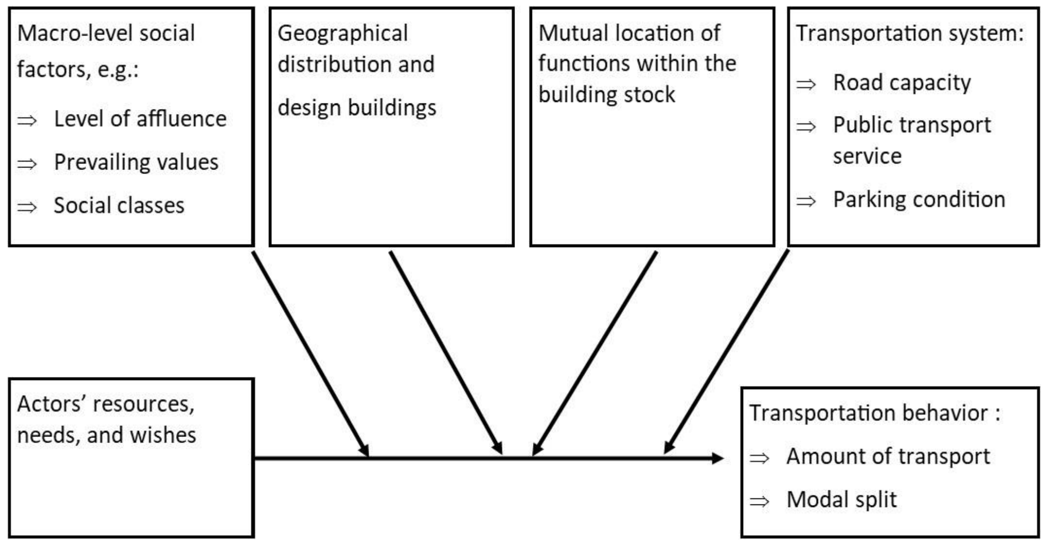

Figure 6. Travel Behavior as A Function of Individual's Characteristics and Land Use

Source: Næss, 2006, p. 11

Analyzing the connection between urban structure and agents is a primary question in social theories and behavioral studies regarding travel behavior (Næss, 2006, p. 12). As shown in Figure 6, modal split is a travel behavior outcome that is affected by various factors such as the built environment, transportation systems, and individual characteristics. Based on Næss's framework, the present research represents a behavioral study for three reasons: First, in this study, individuals' characteristics are examined using disaggregated household survey data, which is a key element of behavioral analysis. Second, built environment factors and the geographical distribution of activities are investigated in this study. Third, this study considers decision-making under congestion, which is missing from traditional four-step models (Stern, 2002). According to Donnelly et al. (2010), analyzing the effects of congestion was one of the reasons for developing behavioral models.

The main purpose of this study is to analyze the effects of traffic congestion on travel behavior. As shown in Næss' framework, congestion is one of the main elements of the transportation system that affect travel behavior. Ultimately, based on the three reasons described above, this research could be considered as a behavioral study, addressing both urban structure and individuals' characteristics as contributory causes of individual travel choice behavior.

Summary

This chapter covered the theoretical background of travel behavior studies and summarized relevant theoretical frameworks, including social theories, transport economics theories, the rational choice paradigm, and the Theory of Planned Behavior. The next chapter shifts from theoretical discussions to the application of these frameworks in the research literature, providing an overview of previous studies and addressing their methodologies, data types, variables considered, and the results of their statistical analyses.

Chapter 3

Literature Review

As mentioned in the previous chapter, travel behavior is a complex phenomenon associated with factors such as individual preferences, attitudes, and urban structures. Understanding travel behavior is necessary for planners and transportation modelers to estimate future travel demand. A considerable literature has been published examining travel behavior and its association with other factors. The following chapter reviews this literature, beginning with a description of the fundamental framework of the interaction between land use and transportation systems. This literature review also covers the ongoing debate about the relative influences of the built environment and the socioeconomic status of travelers on travel behavior, and whether the relationships between these variables are correlative or causal. Ultimately, this literature review provides the framework for the methodology and the selection of explanatory variables in the present study.

This chapter summarizes the literature based on key elements, addressing (1) the built environment, (2) demographics, (3) self-selection, and (4) traffic congestion and their effects on travel behavior. Although traffic congestion play an important role in influencing individuals' travel choice behavior, it has frequently been disregarded in previous studies. The present study builds upon the existing literature by providing additional evidence that factors such as traffic congestion may play an important role in affecting travel behavior.

The Interaction Between Land Use and Transportation System

One of the requirements for developing an integrated land use and transportation model is understanding the interconnections between land use and transportation systems. This understanding helps planners and transportation modelers predict travel demand and provide information for decision makers. In addition to traffic forecasting, these models assist decision makers in considering a variety of scenarios and “what if” questions.

Several models have been developed to simulate the relationship between land use and transportation systems. The first generation of integrated land use and transportation models was known as DRAM\EMPAL (Putman, 1983). Putman’s model is based on Lowry’s (1964) model, which is a gravity model focusing on flows between different locations. DRAM\EMPAL consists of two key components: a Disaggregate Residential Allocation Model (DRAM) and an Employment Allocation Model (EMPAL). In Putman’s Integrated Transportation and Land-Use Package (ITLUP), DRAM allocates households based on the attractiveness of a zone and the accessibility of a zone’s workers to jobs in other zones. In EMPAL, employment during the previous time period and the attractiveness of the zone for households are the principal factors affecting the allocation of employment within the region (Krishnamurthy & Kockelman, 2003). Other examples of land use and transportation models are TRANUS (De la Barra, 1989), MEPLAN (Echenique et al., 1988) MUSSA (Martínez, 1996), and G-LUM (Kockelman et al., 2010).

The integrated land use and transportation models were developed based on several theories of transport geography, urban economics, and behavioral theories (Hanson & Giuliano, 2004; Newman & Kenworthy, 1996). Eliasson and Mattsson (2000) summarized these theories into three groups: urban economics, spatial interaction (or gravity) models, and discrete choice based on random utility theory.

With a focus on city functioning, the core of urban economics is the trade-off between land price and commuting cost, which is described in the bid rent or monocentric model of urban form proposed by Alonso (1964). The origins of the monocentric model of household location can be traced back to the Von Thunen model of land use (also called location theory) in 1826 in a book called "The Isolated State" (Von Thunen, 1826). Based on bid-rent theory, proximity to the workplace and other activities influences the choices of households and firms as they are assumed to maximize their utility (Alonso, 1964). In this framework, firms attempt to locate their businesses next to consumers, resulting in a long-term equilibrium between residential and employment locations. This cost-benefit of external forces is an example of spatial-interdependence between consumers and firms (R. Dubin, 1991; Lucas & Rossi–Hansberg, 2002; Næss, 2006).

The gravity model provides the framework for how distance or proximity influences the distribution of activities and the location of firms and households. According to the spatial interaction (or gravity) models, travel distances and the attractiveness of the destination/activity influence daily trips. As activities and buildings are distributed within the region, the distance between activities results in costs for commuting from one location to another. Since trips are costly, commuters attempt to reduce their trip costs and reside near workplaces.

According to Næss (2006), the urban structure defines the distance between activities and provides facilities for different modes of travel. Therefore, changing the distance between activities can either facilitate or discourage some aspects of travel behavior. Næss (2006) discussed that inner-city dwellers have shorter traveling distances and a higher level of non-motorized trips. This pattern of travel behavior can be explained by the high concentration of jobs, shops, and other activities. This concentration of activities can be explained in several ways, for example via Central Place Theory introduced by Walter Christaller (Christaller, 1966). The agglomeration benefits businesses within the central city, which is related to proximity and lower transportation costs between activities. Local or regional public transport also offer reliable transit services at the central parts of large cities. The concentration of activities in the inner-city area also increases the probability of choosing non-motorized options, taking public transit, and a lower proportion of car travel.

Ultimately, discrete choice models can be used to describe the interaction between land use and transportation systems based on Utility Maximization Theory (Ben-Akiva & Lerman, 1985; Domencich & McFadden, 1975; McFadden, 1974). Traditional travel demand models implement discrete choice models to predict decisions by addressing four steps: whether to travel, destination choice, mode choice, and route choice (de Dios Ortúzar & Willumsen, 2011). The third step, mode choice, examines which mode commuters use to travel between their origins and destinations. Based on the defined utility function, the model estimates whether people take their own car, a carpool, or public transit to and from work or another destination.

Wegener (2004) presented the interaction between land use and transportation and their impacts on individual choices as a two-way interaction loop, arguing that the relationship between land use and transportation is dynamic. This recursive loop presents a dynamic relationship between land use, transport systems, accessibility, and travel behavior (p.130). Figure 7 demonstrates details of the land use/transport feedback cycle. As shown, providing more roads lead to higher accessibility, and accessibility shapes the land use pattern. That is, improving accessibility attracts businesses and households who search for places that are easily accessible. This recursive association is the primary motivation for analyzing the relationship between land use and travel behavior.

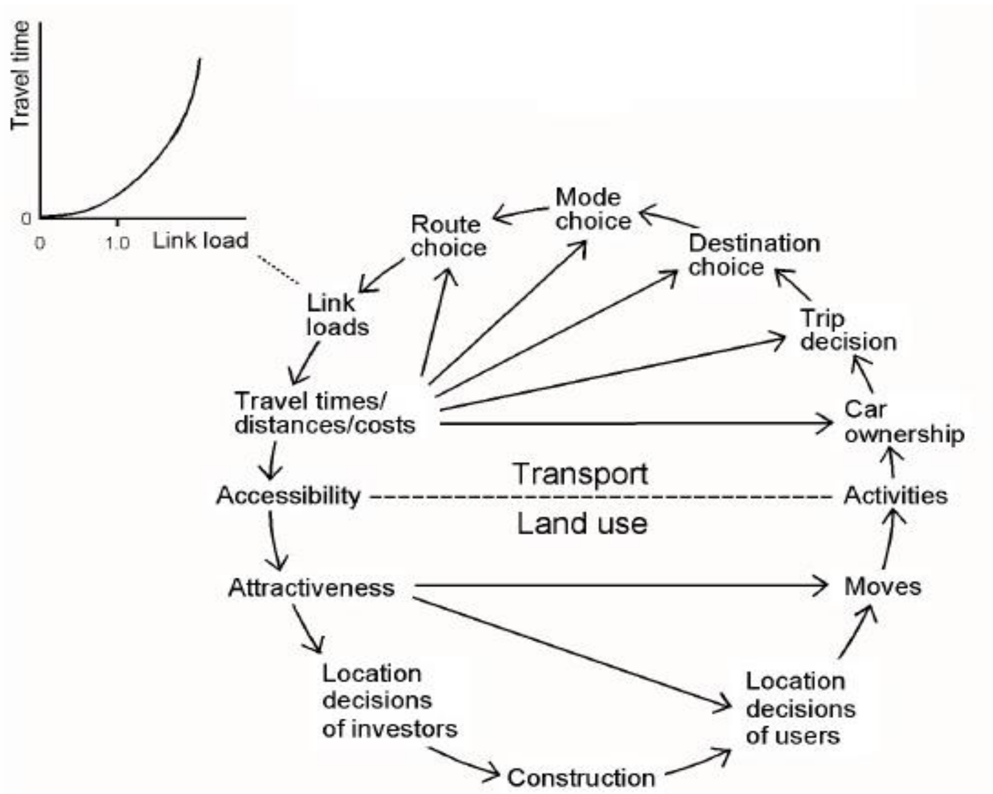

Figure 7. The Land-Use Transport Feedback Cycle

Source: Wegener, 2004

Several other studies have also suggested that this two-way interaction in transportation system (e.g., increasing accessibility or reducing travel cost) affects both land use and travel patterns (Bhiromkaew, 2006; Hanson, 1982; Hanson & Giuliano, 2004). Similar to Wegener (2004), Rose and Martínez (2007) described this association as a recursive relationship, stating that the urban spatial structure defines activity locations and influences travel patterns while travel patterns affect the activity locations.

Modeling individuals' choices is an important component of travel demand models. As illustrated in Figure 7, individual choices can be affected by factors such as accessibility, distance to facilities, and travel times or costs. Also, trip-related choices, including car ownership, trip decision, destination choices, mode choices, and route choices can be influenced by long-term decisions such as residential location. To overcome the limitation of choice models, Lerman (1976), and Dubin and McFadden (1984) developed methods for estimating joint models for continuous/discrete situations. Several joint (mixed) choice models have been developed to consider the impact of household location choice and car ownership (Lerman, 1976; Suel & Polak, 2017; Tran, Zhang, Chikaraishi, & Fujiwara, 2016; Waddell, 1993; Z. Zhang et al., 2017). Other studies have applied cross-nested logit models as joint choice models for simultaneously modeling residential location choice, travel mode, and car ownership (Lemp, Kockelman, & Damien, 2010; Yang, Zheng, & Zhu, 2013).

Ultimately, it should be considered that the unit of analysis for built environment characteristics is a controversial topic in travel behavior studies, because built environment factors at different geographical scales can influence the empirical findings. For example, Cervero and Gorham (1995) observed that mode choice is mostly affected by the characteristics of neighborhoods rather than regional land-use patterns. On the other hand, Boamet and Sarmeinto (1998) and Boamet and Greenwald (2000) found that employment and retail density at a larger scale (i.e., census tracts) have a significant impact on travel behavior.

Built Environment and Travel Behavior

The relationship between the built environment and travel behavior has been the subject of various debates. The study of this topic can be traced to the book “Urban Traffic: A Function of Land Use” by Mitchell and Rapkin (1954). This study was an early attempt to demonstrate how land use patterns affect travel behavior. Mitchell and Rapkin classified the characteristics of traffic movements into a framework, giving particular attention to land-use-based projection techniques. It was the first attempt to explain the basic elements involved in the analysis of land use patterns and the movement of people and goods within urban areas (Chapin, 1955).

Built environment factors that are frequently studied include density, land use diversity, urban form and street patterns, accessibility to jobs, job-housing balance, and distance to facilities such as transit and bike stations (Cervero & Gorham, 1995; Ewing & Cervero, 2001; Greenwald & Boarnet, 2001; Krizek, 2000; Levine, 1998; Newman & Kenworthy, 1989, 1996; Van Acker, Mokhtarian, & Witlox, 2014). Many empirical studies have examined urban structure and found that the built environment, land-use patterns, and urban form can influence travel behavior (Anderson, Kanaroglou, & Miller, 1996; Bagley & Mokhtarian, 2002; Boarnet & Crane, 2001; Cervero, 2002; Cervero & Kockelman, 1997; Chatman, 2003; Ewing & Cervero, 2001; Giuliano & Small, 1993; Golob & Brownstone, 2005; Handy, 1996; Holtzclaw, Clear, Dittmar, Goldstein, & Haas, 2002; Schwanen, Dieleman, & Dijst, 2004).

The potential influences of built environment factors have been found in both aggregate (Cervero & Murakami, 2010; Transportation Research Board, 2009) and disaggregate approaches (Cervero & Duncan, 2003; Cervero & Gorham, 1995; Cervero & Kockelman, 1997; Handy, 1996; Kockelman, 1997). A review of previous studies revealed that certain built environment factors affect travel mode choice, trip frequency, and VMT (Handy et al., 2012). The relationship between the built environment and travel behavior has also been summarized as a series of “D” factors, including density, diversity, design, destination accessibility, and distance to transit (Cervero & Kockelman, 1997; Ewing & Cervero, 2010, 2001). Ewing and Cervero (2010) conducted a comprehensive meta-analysis of the relationship between built environments and travel behavior. Based on the five “D’s,” this meta-analysis provided elasticities for VMT, walking, and transit use, as listed in Table 1. “Elasticity” represents the percentage change in a dependent variable with respect to a given percentage change in the relevant independent variable (de Dios Ortúzar & Willumsen, 2011, p. 43).

Travel distance, such as VMT, is one of the outcomes of travel behavior associated with urban structures. By analyzing travel distances of commuters in the Copenhagen Metropolitan Area, Næss (2006) found that residents who live in the suburbs with a low density of activities tend to travel longer distances with a higher rate of car use than residents located near the city center. As shown in Table 1, “destination accessibility” generally has the greatest influence on VMT, and its elasticity indicates that residents within high-accessibility neighborhoods have lower VMT.

Table 1. Travel Behavior Elasticities with Respect to Built Environment Factors

	Weighted Average Elasticity of:		
Variables	VMT (e)	Walking (e)	Transit Use (e)
Density			
Household/population density	-0.04	0.07	0.07
Job Density	0	0.04	0.01
Commercial floor area ratio	-	0.07	-
Diversity			
Land use mix (entropy index)	-0.09	0.15	0.12
Jobs-housing balance	−0.02	0.19	-
Distance to a store		0.25	-
Design			
Intersection/street density	-0.12	0.39	0.23
% 4-way intersections	-0.12	-0.06	0.29
Destination Accessibility			
Job accessibility	-0.2	0.15	
Job accessibility by transit	-0.05	-	-
Distance to downtown	-0.22	-	-
Distance to Transit			
Distance to nearest transit stop	-0.05	0.15	0.29

Source: Ewing & Cervero, 2010

Walking as a means of transport can be influenced by built environment factors, especially by mixed-use and compact development. As noted in Table 1, land use diversity, accessibility, and distance to public transit are the main built environment factors affecting walking as a means of transport. Kockelman (1997) analyzed the effects of the built environment on vehicle choice and walk/bike choice based on binary dependent variables integrated with logit model assumptions. The results indicate that higher land use balance and higher land use diversity increase the probability of walking/biking among residents (Kockelman, 1997).

Næss (2006) observed that residents within high-density local areas had greater dependence on non-auto modes of transport than residents who live in the suburbs with lower density and land use diversity. He also found that the location of the residence relative to central Copenhagen is the only effective urban structure variable that influences the distance traveled by bike or by foot on weekdays. Additionally, he found that respondents who live in the areas closest to downtown Copenhagen travel an average of 12 miles by non-motorized modes during the weekdays, compared to approximately 8 miles among respondents living 24–28 miles away from downtown. This research indicates that walking/biking is approximately 50 percent higher among residents in the city center.

Transit use is another mode of transport that is influenced by built environment factors. According to a meta-analysis by Ewing and Cervero (2010), transit use is influenced primarily by local densities and secondarily by the degree of land use mixing. The meta-analysis indicates that distance to public transit and design factors such as road and intersection density increase transit use probability. Cervero (2002) examined mode choice decision by developing discrete choice models and testing built environment factors at both residential and employment locations. His findings indicate that non-motorized travel mode choice is dependent on density and land use mix at both origins and destinations. Using data from Boston and Hong Kong, Zhang (2004) found that commuter mode choice is more dependent on the built environment characteristics of the destination than those of the origin. Also, Bhat (1997) developed a joint model of work mode choice and number of stops during the work commute by integrating a multinomial logit model with an ordered-response formulation. This study, which used data from an activity travel survey conducted in the Boston Metropolitan area, indicates that high employment density at the workplace reduces the probability of choosing to drive alone.

Bhat (1997) also found that people who choose to use transit tend to make less non-work stops than those who choose to drive alone.

Similar to the analysis of factors affecting travel distances, Næss (2006) found that residents who live close to the city center have higher rates of choosing non-motorized modes. However, he then showed that the influences of urban structure factors are significantly lower than the effects of car ownership and transport attitude. Not surprisingly, Næss (2006) found that respondents with car-oriented attitudes had higher rates of car ownership, and the proportion of non-motorized travel was lower for these respondents.

Density. Density is one of the built environment factors that is frequently investigated in empirical studies. Density can be examined in terms of population, residence, and jobs. As urban centers are recognized by high rise buildings and mixed-use developments, the degree of urbanization can also be represented by density. Highly dense areas in general are associated with better accessibility to facilities, greater levels of congestion, and transit services. Given these multiple interrelationships, the impact of density on travel behavior has been explored in several studies (Bento, Cropper, Mobarak, & Vinha, 2005; Cervero & Murakami, 2010; Ewing & Cervero, 2010; Gomez-Ibanez et al., 2009). These studies found that density has a negative relationship with automobile use. Also, the modes people choose for travel can be significantly influenced by compact and mixed-use development (Cervero, 2002). By analyzing gross density at both the origins and destinations of trips, Cervero (2002) found that higher gross densities reduced the odds of solo-commuting, especially at the trip destination. According to Brueckner (2000), residents within dense areas with proximity to activities might be encouraged to use available alternative modes such as walking or transit instead of driving.

Auto ownership is another factor affected by density. For instance, Zhang (2005) found that higher population density reduces the probability of auto ownership in Portland and Boston areas. Using disaggregated data from the 1990 National Personal Transportation Study (NPTS), Bento et al. (2005) found that population centrality, an indicator of urban form, has a significant impact on auto ownership. Dunphy and Fisher (1996) and Ross and Dunning (1997) found that residents within high-density areas had higher rates of transit use with fewer and shorter auto trips. Similarly, Næss (2006) observed that areas located close to the city center and high-rise suburban housing with a moderate distance from the inner-city area are more car-dependent, while areas with high car ownership are typically situated in the suburbs of the Copenhagen Metropolitan Area. He also found that the use of public transit is clearly related to density, with residents of dense local areas tending to more extensively use public transit.

Other studies have explored the impact of density on VMT (Bento, Cropper, Mobarak, & Vinha, 2005; Cervero & Murakami, 2010; Ewing & Cervero, 2010; Gomez-Ibanez et al., 2009). These studies have presented an inverse relationship between VMT and density, concluding that residents in dense areas with compact development usually have lower VMT. However, the magnitude of the effect is small in many studies. A meta-analysis by Ewing and Cervero (2010) showed that the elasticity of VMT with respect to residential density is -0.04. This result indicates that VMT is insensitive to density once other socioeconomic and built environment variables are controlled for. In contrast, the National Research Council (2009) found that, on average, doubling residential density is associated with VMT reductions that range from 5 percent to 12 percent. Overall, according to Boarnet and Handy (2014), analyzing the impact of density on VMT implies that doubling density is associated with VMT reductions ranging from 4 to 19 percent.

Diversity. Diversity represents the mixture of land use associated with the distribution of work and non-work activities in a given area (Ewing & Cervero, 2010). Numerous studies indicate that diversity has an important influence on travel mode choice, VMT, and vehicle trips (Boarnet, Nesamani, & Smith, 2003; Cervero & Kockelman, 1997; Chao & Qing, 2011; Ewing, 2008; Ewing & Cervero, 2010; Lin & Yang, 2009). For instance, Ewing and Cervero (2010) found a negative relationship between VMT and land use diversity. Kockelman (1997) investigated mode choice and VMT with factors such as density, entropy index (land use balance), dissimilarity index of land use (mix index), and accessibility. Her findings indicate that accessibility, density, and land use mix are associated with mode choice decisions, especially for non-motorized modes. A study by McCormack, Giles-Corti, and Bulsara (2008) identified that shorter distance between activities enhances walkability within neighborhoods and decreases VMT. Diao and Ferreira Jr. (2014) found the same result, indicating that diversity and the spatial distribution of non-work activities are significantly associated with vehicle usage.

Design*.* Design represents street network characteristics such as street density, sidewalk coverage, and intersection density. Previous studies of design indicate that it is a critical factor influencing household VMT by affecting either the number of miles each car is driven or the number of cars owned (Boarnet et al., 2003; Chatman, 2003; Ewing & Cervero, 2010; Gomez-Ibanez et al., 2009). According to Ewing and Cervero (2010), after the accessibility factor, street design is the most important factor affecting VMT.

Some studies have defined “design” by measuring the shape of the city (i.e., circularity or linearity). For example, analyzing disaggregated household travel survey data in 114 urban areas showed that households in circular cities have lower annual VMT (Bento et al., 2005, p. 475). Walkability is another indicator of design and is most strongly related to measures of intersection density, sidewalk coverage, and the number of destinations within walking distance. According to Diao and Ferreira Jr. (2014), improving the pedestrian environment and providing safe and comfortable sidewalks can decrease VMT and vehicle usage.

In addition to walkability, road density and network connectivity are critical factors that have been investigated in previous studies (Cervero & Kockelman, 1997; Cervero & Murakami, 2010; Diao & Ferreira Jr, 2014). According to Diao and Ferreira Jr. (2014), good connectivity often means a street network provides multiple route alternatives between origins and destinations. Therefore, higher connectivity is associated with lower vehicle usage. Diao and Ferreira Jr. (2014) showed that a good pedestrian environment is related to lower VMT per household and VMT per capita, while its influence on VMT per vehicle is insignificant (2014, p. 3004).

Destination Accessibility. Destination accessibility represents the ease of access to activities, which can be measured by travel time or distance between trip origins and destinations. Kockelman (1997) analyzed travel behavior as a function of accessibility, land use mixing, and land use balance. She used linear models and logit functions to explore vehicle kilometers traveled (VKT), automobile ownership, and mode choice. Then, she examined accessibility by counting the total sales and service jobs within a travel time of 30 minutes. Her findings indicate that accessibility is a far better indicator of VKT and mode choice than density. However, population density was a better factor in Kockelman’s (1997) models of automobile ownership. Likewise, a meta-analysis by Ewing and Cervero (2010) argued that regional accessibility is the most important built environment factor affecting travel behavior, and that VMT/vehicle hours traveled (VHT) is primarily a function of regional accessibility. The meta-analysis indicates a negative elasticity of VMT with respect to measures of destination accessibility (i.e., VMT decreases as destination accessibility improves). The main reason for this negative relationship is low levels of auto ownership and auto dependence at central locations. Also, Ewing and Cervero (2001) found that increasing accessibility or density reduced the trip length of home end trips and non-home end trips.

Accessibility to retail, shopping centers, and other non-work locations affects travel behavior. Crane (1996) observed that short distances to relevant destinations increase trip frequencies due to higher accessibility and lower travel times between origins and destinations. In contrast, when people are faced with a longer distance between their residential location and their destination, they might change their trip plan because they consider the trip to be expensive, cumbersome, and time-consuming (Næss, 2006). Whereas Crane (1996) presented a positive relationship between accessibility to retail and trip frequency, Cervero and Murakami (2010) found that local retail accessibility and access to basic employment reduce VMT. However, they suggest that this relationship is not as strong as population density. In line with Ewing and Cervero (2014), Cervero and Murakami (2010) found that regional accessibility is the most important factor affecting VMT. Furthermore, Diao and Ferreira Jr. (2014, p. 3000) examined accessibility by measuring connectivity, claiming that "good connectivity can improve the connection of people and places and cause shorter local trips, thereby reducing vehicle usage." According to their results, VMT per vehicle, VMT per household, and VMT per capita all increase when the distance to non-work destinations increases.

Distance to Public Transit. Distance to public transit measures the shortest distance from transit stations to home or work locations. Bento et al. (2005) found that increasing rail route miles reduces annual VMT in cities with railroads. Diao and Ferreira Jr. (2014) found a positive relationship between VMT and the "inaccessibility to transit and jobs" factor, concluding that increased distance to public transit increases VMT per vehicle, VMT per household, and VMT per capita.

Ridership is another element of travel behavior that might be influenced by the built environment. For example, Cervero, Ferrell, and Murphy (2002) showed that living and working near transit stations correlates with higher ridership. Næss (2006) found that residents within the suburbs of the Copenhagen Metropolitan Area had the longest commuting distances, the highest car ownership rates, the highest amounts of travel, and the most extensive car use compared to residents located close to the city center.

Socioeconomic Characteristics and Travel Behavior

While most studies have linked travel behavior to land use patterns, other studies have considered the effects of socioeconomics and residential self-selection (Handy, 2005; Walters, Breiland, Jimenez, & Lee, 2012). These studies aimed to examine how individuals perceive the built environment and how their socioeconomic characteristics influence their travel behavior. Some studies have argued that socioeconomic factors have a stronger impact on travel behavior outcomes such as mode choice (Handy, 2005; Cervero, Ferrell, & Murphy, 2002). For example, Handy (2015) claims that the socioeconomic status of commuters is the most important factor affecting commuters' mode choices. In this study, attitudinal variables impacted travel behavior the most among the explanatory variables analyzed (Handy, 2005).

As socioeconomic factors influence travel behavior, they should be considered as control variables in travel demand models. However, gathering travel survey data along with detailed socioeconomic data is expensive and sometimes limited to specific regions. Due to this data limitation, many studies have failed to consider different aspects of socioeconomic characteristics. According to Ewing et al. (1996), omitting socioeconomic factors as control variables results in inaccurate conclusions regarding the actual effects of land use on travel behavior. In other words, this could lead to biased results with either underestimates or overestimates in the statistical analysis (Boarnet & Crane, 2001). Properly considering theoretically relevant variables in the statistical analysis is one solution to such bias (Crown, 1998; Steiner, 1994).

Income is one of the socioeconomic factors that influences individuals' travel mode choices. For low-income workers who do not have access to private cars, public transit is the main mode of transportation (Tilahun & Fan, 2014). Bento et al. (2005) showed that income is positively associated with VMT, with higher income groups exhibiting higher annual VMT. In addition, Diao and Ferreira Jr. (2014) found interesting results related to income; their research found that higher levels of wealth were associated with lower VMT per vehicle but higher VMT per household and VMT per capita. This result is explained by households in wealthier neighborhoods tending to own more cars but driving each car less compared to households in other neighborhoods (Diao & Ferreira Jr., 2014). Furthermore, Brownstone and Golob (2009) showed that fuel usage and household annual mileage have a positive linear relationship with income. They suggest that higher income is associated with higher VMT because of choosing a lower density residential location, greater total driving distances, and the lower impact of fuel price on the household budget. Næss (2006) found that neighborhoods with high income levels had substantially higher rates of car ownership than low income areas.

The life cycle has a significant impact on travel behavior as well. Brownstone and Golob (2009) presented evidence that retired two-person households and households with older children have higher annual VMT because they prefer to live in lower density areas and distance to work is not a concern. In addition, they found that non-retired single-person households had lower annual mileage and fuel consumption, as this group prefers to live in higher-density areas and closer to their workplace. According to Polzin (2006), larger households have a higher likelihood of carpooling, which results in additional person trips without additional vehicle trips. According to this research, the VMT of single person households is half that of two-person households. This may be a result of the fact that “many single person households are elderly persons living alone who are not very mobile and other individuals who have chosen a more solitary lifestyle” (Polzin, 2006, p. 9).

Education has also been shown to affect travel behavior. For example, Brownstone and Golob (2009) found that households headed by an individual with a college degree or postgraduate degree have higher annual VMT and fuel usage. Furthermore, Brownstone and Golob (2009) found that the number of household drivers has a strong impact on household annual mileage as well as fuel consumption. They also showed that household annual mileage increases with the number of children.

Household size, number of children, and the number of working adults are statistically significant predictors of VMT and mode choice in most studies (Bento et al., 2005; Brownstone & Golob, 2009; Diao & Ferreira Jr, 2014). For example, Bento et al. (2005, p. 475) confirmed that the number of persons and working adults in a household has a significant impact on annual VMT per vehicle. They also found that households with children (age less than 16) had higher annual VMTs. Additionally, their research indicated that race (white or black household) was not a statistically significant predictor of VMT. Another study by Diao and Ferreira Jr. (2014) showed that the number of children in the household is positively associated with household VMT. However, they found that the impact of children on VMT per vehicle and VMT per capita is insignificant. One explanation they posited for this result is that households tend to buy more vehicles as household size grows, but the usage of each vehicle does not change significantly. In contrast to the number of children, their study found that working status had a strong impact on VMT per vehicle, VMT per household, and VMT per capita.

Age, gender, race, and ethnicity are additional socioeconomic factors that can affect travel behavior (Basarić, Vujičić, Simić, Bogdanović, & Saulić, 2016; Brownstone & Golob, 2009; Tilley & Houston, 2016). According to Brownstone and Golob (2009), Black, Hispanic, and Asian households tend to settle in higher-density areas than White households, resulting in lower fuel consumption and vehicle usage for these groups. Gender and age differences in travel behavior have also been investigated in various studies (Bagley & Mokhtarian, 2002; Cao, Mokhtarian, & Handy, 2009; Kitamura et al., 1997; Sánchez & González, 2016; Tilley & Houston, 2016; Van Acker et al., 2014). Using descriptive analysis, Tilley and Houston (2016) investigated mobility trends between the mid-1990s and the mid-2000s by age group, gender, and birth cohort. Their results indicate that younger cohorts of women travel farther as they age.

Immigration status is another socioeconomic factor that has been investigated in several studies (Chatman & Klein, 2013; Tal & Handy, 2010). Employing 2001 National Household Travel Survey (NHTS) data, Tal and Handy (2010) investigated the correlation between travel behavior and immigrant characteristics measured by year of immigration to the U.S. and place of birth. Controlling for spatial and socio-demographic variables, Tal and Handy (2010) found that:

> …socio-demographic variables have different effects on car ownership for some of the immigrant groups: household size, households with no children, and retired households have negative effects on auto ownership for immigrants from Central and South America and from East Asia. All three effects may relate to lower need for a car relative to others in the same immigrant group but also suggest greater constraints on car ownership than for respondents with the same demographic characteristics in other immigrant groups (p.90).

Residential Self-Selection

Decisions, such as residential self-selection, have recently come under critical observation as important potential contributors to influencing individuals' travel behaviors. Several studies have been conducted to examine the effects of built environment characteristics on travel behavior. However, the study of how individuals' attitudes and perceptions affect their travel behaviors is a controversial topic. As mentioned in the land-use transport feedback cycle (Wegener, 2004), travel behavior is associated with interrelated decisions such as choosing a residential location and car ownership. Several studies have argued that individuals' decisions for choosing a specific residential location or owning a car could influence their modes of travel (Boarnet & Crane, 2001; Bohte, Maat, & Wee, 2007; Lerman, 1976; Schwanen & Mokhtarian, 2005; Srinivasan & Ferreira, 2002; J. Zhang & Van Acker, 2017).

To reduce the uncertainty of land use and transportation models, it is necessary to consider individuals' decisions and separate out the self-selection bias from the analysis. Schwanen and Mokhtarian (2005) argued that travel behavior studies could lead to biased and inconsistent results if built environment attributes were investigated without considering the effects of self-selection issues. According to Handy (2005, p. 23), "Attitudinal variables have the greatest impact on travel behavior among all of the explanatory variables and residential location type has little impact on travel behavior". Handy (2005) concluded that the connection between travel behavior and residential type is better explained by self-selection, as residents with certain attitudes are moving to certain kinds of neighborhoods. Based on a qualitative study of several interviewees living in inner-city locations in the Copenhagen Metropolitan Area, Næss (2006) observed that these residents chose to use the bikes as their main mode of travel and have even chosen not to own a car. Næss (2006) explained that for these interviewees, saving time, saving money, maintaining physical stamina, and maintaining local social contacts are the main reasons for limiting travel distances.

Due to the availability of data, most empirical studies have disregarded the important role of long-term decisions such as residential location choice. Using disaggregated data, several studies have examined attitudinal factors toward residential and workplace locations (Bagley & Mokhtarian, 2002; Cao et al., 2009; Ettema & Nieuwenhuis, 2017; Lerman, 1976; Van Wee, 2009). Analyzing residential self-selection requires specific data that present the complex interdependencies of travel behavior outcomes, lifestyle decisions, and attitudes towards travel and residential location (Van Acker et al., 2014). According to Van Acker et al. (2014), travel behavior should be examined within a hierarchy of choices while investigating the motivational background of these decisions. This interrelationship causes the complicated issue of self-selection.

Various cross-sectional studies have noted that residential self-selection influences travel behavior (Bagley & Mokhtarian, 2002; Boarnet, 2011; Cao et al., 2009; Chatman, 2003; Handy, Cao, & Mokhtarian, 2005; Handy & Clifton, 2001). These studies attempted to determine whether individual preferences influence choosing neighborhoods within cities and whether neighborhood characteristics affect travel behavior. Different approaches can be used to consider the impact of residential location choices. For example, studies have incorporated demographic and land use variables combined with instrumental variables (Boarnet & Greenwald, 2000; Boarnet & Sarmiento, 1998; Greenwald & Boarnet, 2001), attitudinal factors (Ettema & Nieuwenhuis, 2017; Kitamura et al., 1997; Kuppam, Pendyala, & Rahman, 1999; J. Zhang & Van Acker, 2017), and longitudinal travel data or panel data (Beige & Axhausen, 2017; Handy et al., 2005; Krizek, 2000; Srinivasan & Ferreira, 2002). Besides the variety of data, these studies have also implemented different statistical methods such as nested logit models (Cervero

& Duncan, 2003; Eliasson & Mattsson, 2000; Peng, Dueker, & Strathman, 1996) and the SEM approach (Bagley & Mokhtarian, 2002; Van Acker et al., 2014) to address residential location choices with travel demand models. Using SEM, Van Acker et al. (2014) found a significant direct effect of residential neighborhood on car ownership. Ultimately, Cao and Mokhtarian (2005) summarized the methodologies best suited for attitudinal self-selection analysis into nine categories: instrumental variable models, direct questioning, statistical control, sample selection models, joint discrete choice models, SEM, propensity scores, mutually-dependent discrete choice models, and longitudinal designs. In addition to residential selection, some studies have considered the effects of other decisions such as car ownership. For instance, Small and Winston (1999) discussed that mode choice and car use might be associated by the number of automobiles owned by a household.

There are two types of empirical approaches frequently used in travel behavior studies; aggregation and disaggregation approaches. Aggregating travel survey data by geographical areas such as TAZs, neighborhoods, and urban areas leads to the possibility of overlooking residential self-selection. Aggregation approaches assume homogeneity among individual and built environment attributes. They do not allow variation across different observed individuals and elements of built environment characteristics within geographical zones (Bhiromkaew, 2006). In contrast, the use of disaggregation approaches provides information about individuals' travel behaviors that aid researchers in capturing more variability in their analyses. However, understanding residential self-selection is not a straightforward process due to various uncertainties and unobserved variables.

One approach to understanding residential self-selection is designing a questionnaire that includes questions that capture the preferences, attitudes, and behaviors of commuters (Bagley & Mokhtarian, 2002; Kitamura et al., 1997). For example, Bagley and Mokhtarian (2002, p. 281) surveyed individuals' responses to 39 statements measuring attitudes toward private automobile use, ridesharing, public transportation, housing preferences, and economic policies to understand household attitudes. They ultimately found that when attitudinal, lifestyle, and socio-demographic variables were accounted for, neighborhood type had little influence on travel behavior. Furthermore, Kitamura et al. (1997) concluded that:

> "… attitudes are certainly more strongly, and perhaps more directly, associated with travel than are land use characteristics. This suggests that land use policies promoting higher densities and mixtures may not alter travel demand materially unless residents' attitudes are also changed" (p.156).

Previous studies have often been criticized for the lack of investigation into whether a causal relationship exists between urban structure and travel behavior. According to Handy (1996), there are several limitations with aggregated data that prevent identifying the mechanisms of how built environment characteristics influence travel decisions. One of the limitations of aggregated data is that they cannot indicate causal relationships (Handy, 1996, 2005).

On the other hand, disaggregation approaches provide an opportunity to examine the effects of personal attitudes and preferences on travel outcomes. The benefit of using disaggregated data is the ability to associate socioeconomic characteristics of commuters with travel outcomes. With the use of personal characteristics and built environment factors on smaller scales, the primary focus of the disaggregate approach is to explain unobserved factors which are not considered in aggregation approaches. As the estimated coefficients are directly related to individuals, the findings from disaggregated data can be used to determine causality among variables (Handy, 1996).

Urban Structure, Travel Time, and Congestion

Congestion is considered one of the major problems of urban transportation, as it has grown not only in the largest cities but in cities of every size. Over the last several decades, commuters have been challenged with increasing travel times, inconvenience, stress, and expenses for fuel and taxes (to fund possible solutions to congestion). In 1990, the report “Effects of Congestion On Mobility In New Jersey” presented by Senator Lautenberg highlighted congestion as a serious problem that requires serious efforts by the federal government, state governments, local governments, and the private sector (U.S. Senate, Subcommittee on Transportation and Related Agencies, 1990). Congestion and delays have a straightforward effect on travel time and speed, which planners and decision makers evaluate for long-term projects. Changes in suburban development, automobile use, and high-speed highway infrastructure have encouraged auto dependency in the United States, with negative outcomes such as increasing traffic congestion across urban areas. According to the Federal Highway Administration (FHWA), congestion is the result of seven root causes that are interrelated: traffic incidents, work zones, weather, fluctuations in normal traffic (demand), special events (demand), traffic control devices, and physical bottlenecks (capacity) (U.S Department of Transportation, Federal Highway Administration, 2015) In addition to these factors, urban form and land use patterns influence the level of traffic congestion.

The impact of urban structure on travel time and congestion has been widely investigated in previous studies (Brinkman, 2016; Kuzmyak, 2012; Sarzynski et al., 2006; Schwanen, Dijst, & Dieleman, 2001). The conventional wisdom about congestion and land use considers suburbanization as the stimulating engine which increases traffic congestion. According to this wisdom, a low density of housing and workplaces encourages longer commutes with higher trip frequencies, thereby imposing a higher level of traffic congestion (Downs, 1992). On the other hand, it has been argued that suburbanization results in shorter trips and lower VMT with higher average speeds, which leads to less traffic congestion (Gordon et al., 1991).

Sarzynski et al. (2006) examined the conventional wisdom and the effects of land use on traffic congestion using aggregated urbanized data. In contrast to conventional wisdom, they found that denser urban areas with a cluster of activities have higher auto volumes and traffic delays. In this study, Sarzynski et al. (2006) showed that urban areas with higher densities and housing centrality tend to have more traffic congestion.

Considering urban structure, Bovy and Salomon (2002) explained traffic congestion based on supply and demand by addressing multiple interrelated factors such as economic factors, transport supply, socio-demographics, and urban spatial structure. As presented in Figure 8, spatial structure and transport supply influence car use, and car use directly affects traffic congestion. Also, socioeconomic factors, transport supply, and spatial structure indirectly influence traffic congestion by their direct impacts on car use. This framework defined traffic congestion as a self-reinforcing process with short-term and long-term feedback loops influencing car use (Bovy & Salmon, 2002). Based on this framework, the congestion/land use feedback loop can be interpreted as the same as the Land-use transport feedback cycle (Wegener, 2004). Additionally, Bovy and Salomon (2002) discussed that suburbanization provides lower housing costs, which increases travel distances and population growth, causing a higher number of trips within the region. These two factors have resulted in growing demand for road space and have necessitated improvements or extensions of the current transport system.

Simultaneously, the roadway improvements provide higher accessibility, which leads to lower car costs per VMT and increased car ownership. In this dynamical system, traffic congestion increases the demand for roads and providing more roads is directly associated with higher accessibility and land use development. Figure 8 explicitly demonstrates a simplified dynamic model of endogenous and exogenous factors contributing to congestion.

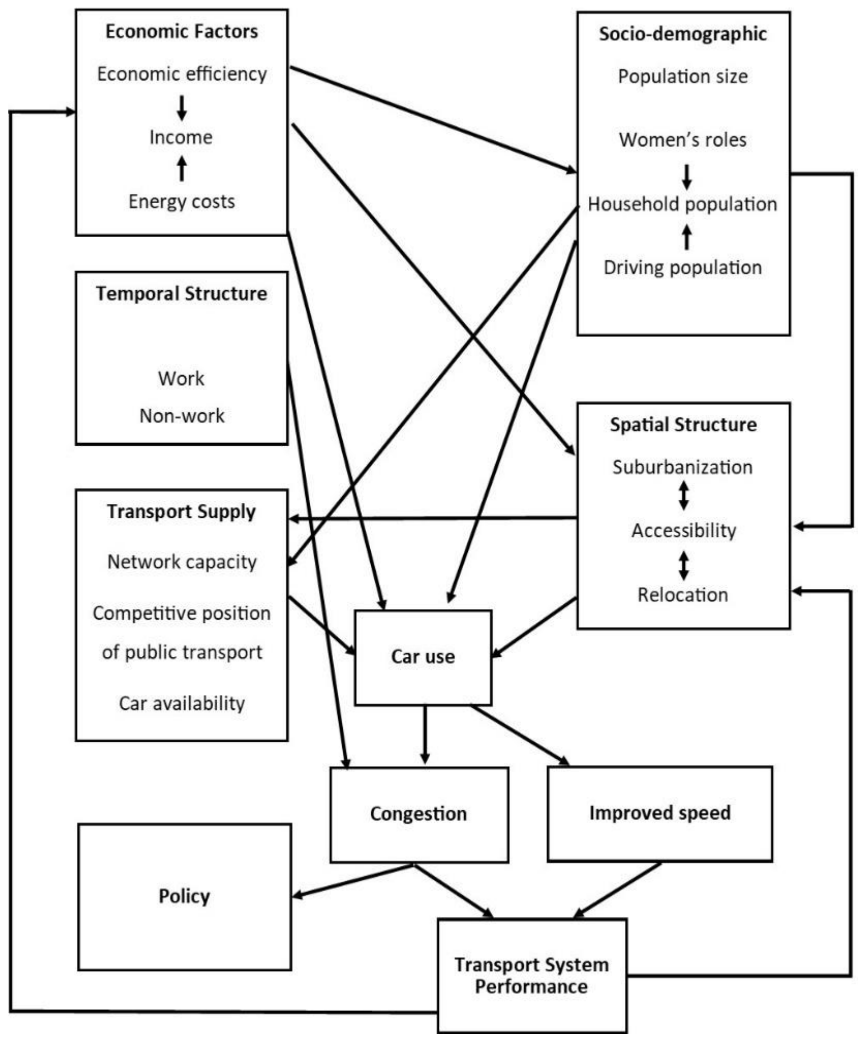

Figure 8. Main External Factors Affecting Congestion

Source: Bovy & Salomon, 2002

Congestion and Travel Behavior

Understanding traffic congestion and its impact on commuter travel behavior is a critical factor in transportation planning. Traffic congestion influences different aspects of travel behavior, including VMT, VHT, PMT, and mode choice. In addition to travel behavior, traveling within a region with a congested road is associated with increased stress, low physical activity, and infant health problems (Currie & Walker, 2011; Levy, Buonocore, & Von Stackelberg, 2010; U. S. General Accounting Office, 1989). Congestion and delays are often defined as the "impedance" for the movement of people and goods, which can be measured in terms of travel distance, travel time, and speed. Traffic congestion increases travel times and travel costs, therefore influencing commuter's travel behavior. Based on Utility Maximization Theory (Ben-Akiva & Lerman, 1985; Domencich & McFadden, 1975; McFadden, 1974), commuters try to minimize these costs and maximize benefits by changing the timing of their trips, selecting different modes, or canceling their unnecessary trips.

To investigate the effects of traffic congestion on commuters' choices, it is useful to consider a system dynamics model presented by Bovy and Salomon (2002). Figure 9 demonstrates a simplified system dynamics model of land use, transport, and demographic factors contributing to car use, car ownership, and mode choice. As shown, car use and car ownership are the components of this system dynamics model and are affected by income and other factors such as economic activities and land use patterns. In this system, congestion affects the efficiency of transport by increasing both travel times and trip costs. According to Utility Maximization Theory, maximizing comfort and minimizing travel time and cost and are the key determinants of motorized travel (Committee on Physical Activity, Health, Transportation, and Land Use, Transportation, 2005). That is, commuters prefer non-auto options to minimize their trip costs within congested areas.

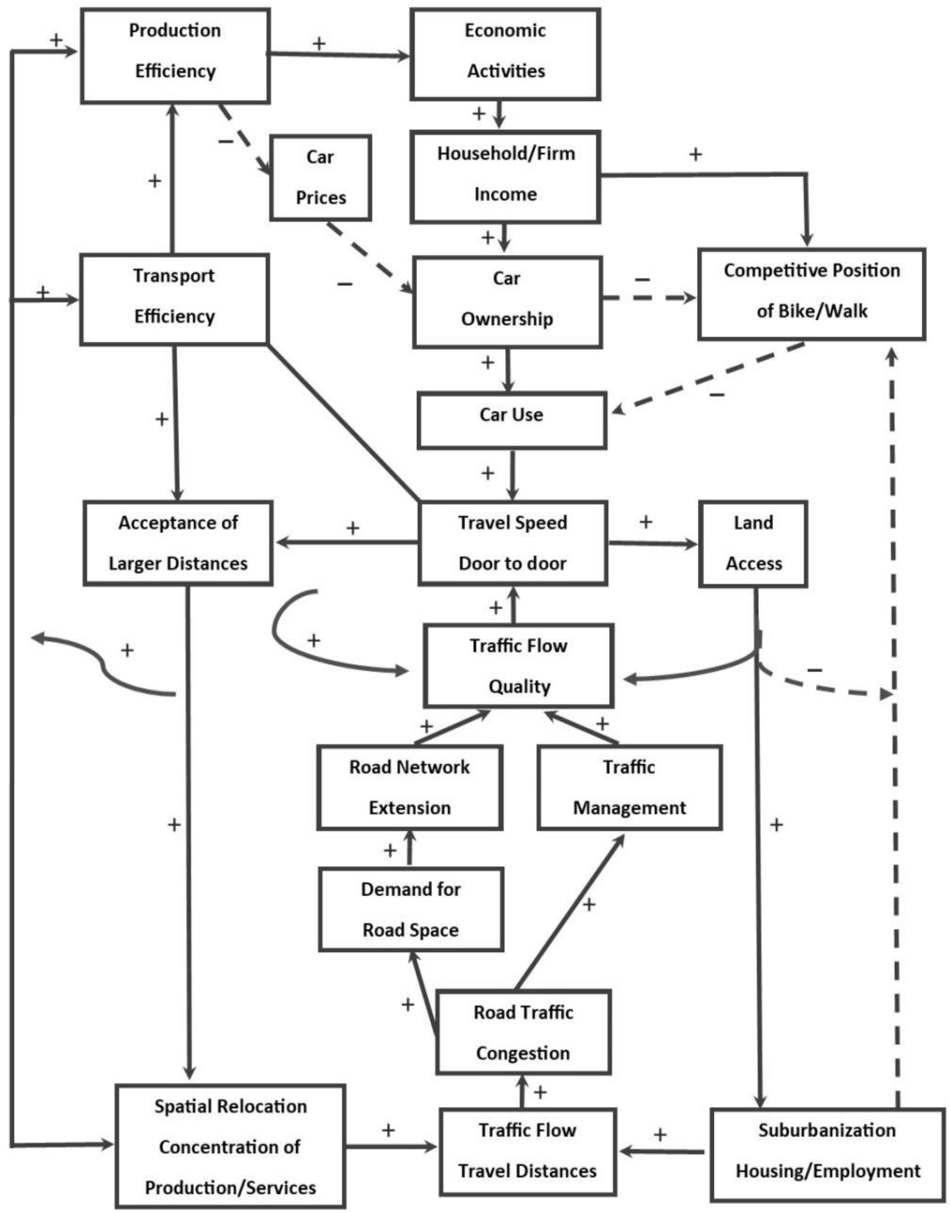

Figure 9. System Dynamics Model of Factors Contributing to Mode Choice and Car Ownership

Source: Bovy & Salomon, 2002, p. 149

Although traffic congestion is an important factor that affects travel behavior, only a few studies have quantified the impact of congestion on travel behavior (Davis, 2004; Kuzmyak, 2012; Litman & Colman, 2001; Næss, 2006; Sweet & Chen, 2011). These empirical studies presented that monetary costs and reduced time consumption are effective factors that influence commuters' choice of travel. For example, Litman and Colman (2001) found that reducing traffic congestion generates traffic and encourages more vehicle travel by reducing the generalized cost of driving. Sweet and Chen (2011) investigated the effects of traffic congestion on taking public transit and found that higher traffic congestion and unreliable auto travel conditions induce mode switching to public transit when service by train is already faster than by car. Næss (2006) observed the same results in Copenhagen, with some interviewees choosing to take a train during rush hours to avoid spending time in traffic congestion and choosing to drive by car to downtown when commuting during off-peak hours. Næss (2006) also noted that several inner-city interviewees selected a bike as their means of transport because it is faster than car to reach destination up to 4 miles from their home location. By investigating four Phoenix transportation corridors, Kuzmyak (2012) found that residents in higher-density neighborhoods with traffic congestion on adjacent streets make substantially shorter trips. This research also indicated that average trip length for home-based trip is about 7.4 miles in higher-density neighborhoods compared to 10.7 miles in suburban neighborhoods. To examine the impact of traffic congestion on household behavior, Davis (2004) focused on commuting time as the outcome of joint residential and employment decisions. This study indicates that congestion plays an important role in affecting travel behavior by influencing household's decisions for the selection of residential location.

Traffic congestion might suppress vehicle usage because of higher travel times and costs. A recent study by Ewing et al. (2017) investigated the relationship between compact development, VMT, and traffic congestion. Although their research explored the relationship between VMT and total delay (as a measure of traffic congestion), the findings did not present individuals' travel behaviors, as it was based on aggregated total delay and total VMT for urbanized areas. Using disaggregated 2009 NHTS data, Sardari, Hamidi, and Pouladi (2018) found an inverse relationship between VMT and traffic congestion around household home locations.

Measuring the effects of traffic congestion on travel behavior is critical for determining the relationship between highway capacity improvements and traffic congestion. According to Diao and Ferreira Jr. (2014, p. 3000), decreasing the cost of personal vehicle travel by providing higher speed limits or widening roads can increase vehicle usage. In addition to highway capacity improvements, the relationship between congestion pricing and travel behavior has been investigated in several studies (Brinkman, 2016; Deakin, 1994; Harvey, 1994; Linn, Wang, & Xie, 2016; W. Zhang & Kockelman, 2016). For instance, Zhang and Kockelman (2016) developed land use models, based on the bid-rent theory, to simulate the impact of congestion pricing scenarios on firm and household location choices and rent distributions. The results of the model indicate that road pricing policies have significant impacts on households and firms' equilibrium distributions (W. Zhang & Kockelman, 2016).

The following section presents the methodology of calculating time-related mobility measures and developing a generalized SE model to explore the relationship between traffic congestion and travel mode choice for journey to work trips.

Measuring Traffic Congestion

Measuring traffic congestion is the first step to examining a transportation system and its performance within urban areas. Several performance measures have been developed to measure and track traffic congestion. Mobility analysis can be conducted by examining the travel time index, travel rate index, total delay, and accessibility as primary measures (Cambridge Systematics, Inc., 2005; Lomax & Schrank, 2002; Lomax, Turner, & Shunk, 1997; Schrank et al., 2005; Turner, Lomax, & Levinson, 1996). According to the National Cooperative Highway Research Program (NCHRP) report 398, travel-time-based measures are a reliable and preferable approach to estimating and presenting mobility and congestion information. However, the main issue of travel time measures is "where are the data?"(Lomax et al., 1997). Conventional level of service (LOS) measures use road characteristics, such as number of lanes, facility type, and area type, to measure capacity and LOS. With new techniques and data such as GPS and cell phone data, using travel time data helps to enhance analyses of real-time transportation performance. As reported in the *NCHRP Report 398*, the measurement of mobility can be implemented in seven categories, which are presented in Table 2.

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Table 2. Different Scale of Using Mobility Measurement

Geographic Scope	Intersection/Interchange	Location	CBD Core, CBD Fringe
	Facility Segment		Central City
	Route/Corridor		Suburbs
	Sector/Subregion		Suburban Fringe
	Region		Seasonal/Resort
	State/Nation		Stadium, Arena or Sports Complex
Transportation Mode	Roadways	Roadway Type	Freeways and Toll Roads
	HOV or Bus-Only Lanes		Expressways and Super Arterials
	HOT Lanes, Managed Lanes		Principal Arterials
	Car Pools, Buses		Minor Arterials
	Rail in Roadway or Median		Collectors
	Exclusive Guideway Transit		Local Streets
Time of Day / Day of Week	Morning Peak, Afternoon Peak, Noon Peak	Planning Context	Existing Conditions
	Midday, Evening		Existing Demand/Modified Supply
	Daily Average		Future Demand/Existing Supply
	Weekday Average		Future Year Conditions
	Special Events, Holiday or Weekend	Level of Detail	Policy, Planning, Design, Operations

Note: HOV: High-Occupancy Vehicle; HOT: High-Occupancy Toll Lane
Source: Lomax et al., 1997

Mobility can be assessed by analyses of speed and travel rates. Although travel time and speed information are the most reliable measures of transportation performance, these data are not always available. According to Schrank et al. (2005), congestion performance measures must be based on measurements of travel time. In contrast to LOS and VOC indices, travel time data can be easily interpreted by different groups or audiences. Figure 10 presents how travel times can be measured from different data and analytical methods.

According to Schrank et al. (2005), the best methods for calculating travel times between origins and destinations are based on direct measurements of travel time, either through probe vehicles (e.g., toll tags and cellular telephones) or the “floating car” method (as a traditional approach). Figure 10 illustrates how travel times can be transformed into a variety of performance measures such as travel time index, buffer time index, and planning time index.

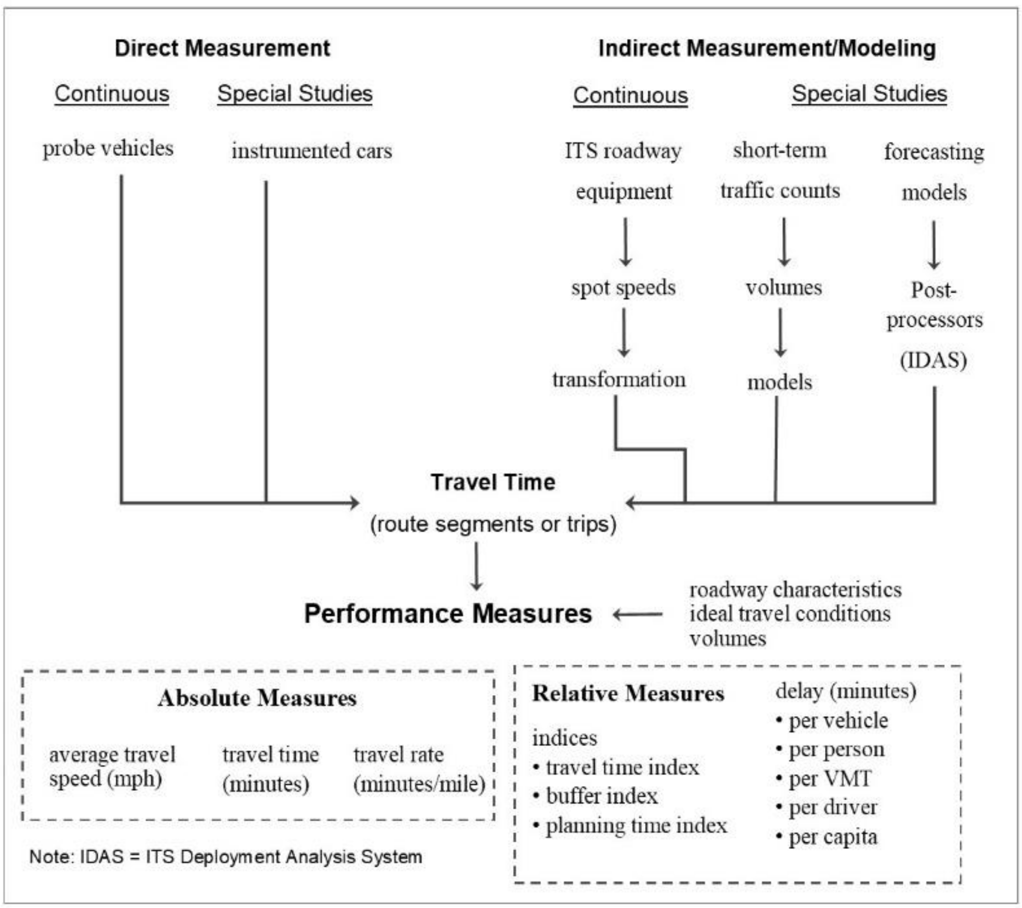

Figure 10. Time-Related Mobility Measures
Source: Turner et al., 1996

Travel time and speed are key components to measuring the performance of a transportation system. As shown in Figure 10, travel-time-based performance measures can be classified into two groups: 1) absolute measures and 2) relative measures. Absolute measures include factors such as actual speed and travel time, whereas relative measures require comparison to the basic conditions such as posted speed limit or “free-flow” conditions (Turner et al., 1996).

Transportation performance measures can be categorized into two levels: individual measures and area mobility measures. Individual measures are related to the individual traveler, whereas area measures present congestion by geographic level (e.g., a corridor or region). Congestion can be expressed by travelers’ waste time due to congestion or extra traffic volume on road segments within high demand regions such as CBDs. Some measures of traffic congestion consider individual commuters and their total delay and extra travel time spent during their trips. According to Schrank et al. (2005), the calculation of individual measures is often based on the Transportation Research Board’s (TRB) current Highway Capacity Manual (HCM) analysis techniques, vehicle density measures calculated from detectors in the pavement, or aerial surveys, Also, roadway characteristics and/or speed data from available traffic volumes can be used to estimate individual measures. As mentioned before, collecting travel time and speed data are somewhat more difficult than collecting traffic volume counts (Schrank et al., 2005). As a result, most transportation performance measures are calculated based on traffic volume counts. Table 3 summarizes these measures by level of analysis. The definitions of transportation performance measures are reported in Appendix A.

Table 3. Transportation Performance Measures

Performance Measure	Geographic Area
Delay per Traveler	Region, Sub-Area, Section, Corridor
Travel Time Index	Region, Sub-Area, Section, Corridor
Buffer Index	Region, Sub-Area, Section, Corridor
Total Delay	Region, Sub-Area, Section, Corridor
Congested Travel	Region, Sub-Area
Percentage of Congested Travel	Region, Sub-Area
Congested Roadway	Region, Sub-Area
Accessibility	Region, Sub-Area

Source: Lomax et al., 1999

Comparison of Mobility Measures

As mentioned earlier, there are different mobility measures which can be investigated at different geographic levels. According to previous studies, using time-related measures and speed data are the best sources for measuring mobility (Schrank et al., 2005). Schrank et al. (2005) classified the usage of mobility measures by several types of analyses and area sizes. As shown in Table 4, transportation performance measures such as travel time and travel rate are beneficial for analyses up to the corridor level, while delay and accessibility measures are useful for analyses at higher levels. According to Schrank et al. (2005), total delay, delay per person, and travel time difference are practical measures for small-scale analyses.

Table 4. Recommended Mobility Measures

Analysis Area	Mobility Measures*								
	Travel Time	Travel Rate	Delay per Traveler	Travel Time Index	Buffer Index	Total Delay	Congested Travel	Percentage of Congested	Accessibility
Individual locations	S		P	P	P	P			
Short roadway sections	P	P	P	P	P	P			
Long roadway sections		S	P	P	P	P			
Corridors		S	S	P	P	P			S
Sub-areas		S		P	P	P	P	P	P
Regional network		S		P	P	P	P	P	P
Multimodal analysis		S	S	P	P	P			P

*Note: P = Primary mobility measure; S = Secondary mobility measure
Measures with delay components can be calculated relative to free-flow or posted speed conditions.
Sources: Schrank et al., 2005

Summary

This chapter provided an overview of previous studies addressing their methodologies, data, variables, and statistical results. Specifically, this chapter reviewed literature with a focus on the interaction between land use and transportation systems, and the effects of socioeconomic characteristics and residential self-selection on travel behavior. In addition, this chapter discussed the process of measuring traffic congestion and compared different mobility measures. Comparing mobility measures presented that using time-related measures and speed data are the best sources for measuring mobility. The next chapter reviews the statistical approach of this study and covers the process of data integration.

Chapter 4

Methodology and Data

Introduction

Measuring and monitoring traffic congestion is a vital aspect of transportation performance management. Transportation planners and agencies are interested in knowing about the effects of traffic congestion on mobility and how to develop plans based on future demand. From a modeling perspective, travel demand modelers are interested in understanding the effects of congestion on travel behavior. This understanding helps them improve travel demand models such as activity-based models and enhanced mode choice models. However, analyzing the effects of congestion on travel behavior is associated with several limitations, as described below.

The first issue is associated with data aggregation. Examining travel behavior requires detailed data about individuals and their preferences and daily commute patterns. To overcome data aggregation bias, the present study used disaggregated travel survey data with detailed information about the origins and destinations of commuters.

High correlations between the independent variables is the second limitation of travel behavior studies. Built environment factors tend to be highly correlated to one another when they are all included in a model. This study attempts to address this issue by using structural equation modeling (SEM) to deal with the high correlation of land use characteristics.

The third issue is related to the discrete choice analysis in the structural equation (SE) model. The outcome variables in an SE model should be continuous variables. In this study, the generalized structural equation modeling (GSEM) method was used to develop choice models with discrete outcomes.

The fourth problem of travel behavior studies is related to the effects of long-term and mid-term decisions on short-term decisions. The reciprocal relationship between mode choice decisions and other decisions might influence the commuter's mode choice. For example, residential location choice (as a long-term decision) and car ownership (as a mid-term decision) influence mode choice decisions. This effect is the so-called "self-selection" problem. To avoid a biased analysis, it is necessary to investigate the effects of long-term, mid-term, and short-term decisions and consider the interrelationship between mode choice, car ownership, and residential location choice. This study has the advantage of using residential preference data extracted from the PSRC travel survey.

The fifth issue relates to the absence of time-related mobility measures when modeling VMT or travel mode choice, thereby leaving the effects of congestion on VMT or mode choice unexplained. Analyzing time-related or speed-related mobility data during the off-peak and peak periods is the missing factor of previous studies. The volume-over-capacity (V/C) ratio is one measure that can be used as a proxy for the level of traffic congestion. However, this factor does not directly represent actual travel time delay. New technologies such as cellphone data and GPS data provides an opportunity to analyze population mobility at small geographic levels and investigate the effects of congestion on commuter travel behavior. The present study has the advantage of using travel time delay data extracted from the Google Maps Distance Matrix API. Google Maps travel time data are based on GPS and cellular telephones, presenting historical traffic condition and measuring travel time directly.

This chapter begins with a description of the present study's statistical framework, which explains the modeling techniques used to analyze VMT and travel modes along with residential self-section factors. This section reviews the fundamental frameworks of structural models and discrete choice modeling, which are then extended to GSEM.

The second section of this chapter describes the process of data gathering, cleaning, and integration. In this section, the explanatory variables in the VMT and mode choice models are explained along with their descriptive statistics derived from built environment and travel survey data. Figure 11 summarizes the statistical approaches and data integration described in this chapter.

Methodology Statistical Approaches

- Structural Equation Modelling (SEM)
- Multinomial Logit (MNL) Model
- Generalized Structural Equation Modelling (GSEM)

Data Data Integration

- Household Travel Survey Data
- Residential Preference
- Built Environment Data
- Travel Time Delay Data

Figure 11. Methodology and Data

Statistical Approaches

To examine the potential interactions between the built environment and travel behavior, empirical studies have applied various methodologies ranging from simple regression models to advanced techniques such as SE models. In order to examine the travel behavior of individuals, classical linear regression models are the most common method used. Classical linear regression with ordinary least squares estimation is commonly implemented to analyze continuous travel outcomes such as VMT, trip frequency, and PMT. To analyze discrete outcomes such as mode choice, multinomial logit (MNL) and nested logit (NL) models are the primary techniques for exploring the probability of choosing a specific mode over other alternatives. MNL and NL models have been used in various studies to estimate discrete choices involving routes, destination, modes, and residential location choices (Bhiromkaew, 2006; Cervero, 2002; Cervero & Duncan, 2006; J. Chen & Li, 2017; Fatmi & Habib, 2017; Peng et al., 1996; Schwanen & Mokhtarian, 2005; Soltani, 2017; Srinivasan & Ferreira, 2002; Yang et al., 2013; Zaman, 2010).

The econometric theory of random utility maximization is the main framework of discrete choice analysis as implemented in various travel choice studies (Ben-Akiva & Bierlaire, 2003; Cervero, 2002; C. Chen, Gong, & Paaswell, 2007; Horowitz, 1980; Hsu, 2013; Xu, 2011). According to Koppelman and Bhat (2006), utility is an indicator of value to an individual. The utility maximization rule assumes that an individual will choose the alternative from his/her set of available alternatives that maximizes his or her utility level (p. 14). The rule also indicates that “there is a function containing attributes of alternatives and characteristics of individuals that describes an individual’s utility valuation for each alternative” (p.14).

The utility function can be classified into components that are (1) completely related to the attributes of alternatives, (2) fully related to the characteristics of the decision maker, and (3) represent interactions between the attributes of alternatives and the characteristics of the decision maker (Koppelman & Bhat, 2006). Each alternative has different attributes that influence an individual’s decision to select an alternative. These attributes include measures such as travel time, travel cost, the reliability of on-time arrival, walk access distance, distance to public transit, and others.

The MNL model is the main component of discrete choice models. However, it assumes the independence of irrelevant alternatives (IIA). The IIA property results from the assumptions about the random component in the MNL model. In the MNL model, the random component is supposed to be independent and identically distributed (IID) (Ben-Akiva & Lerman, 1985). IID indicates that the random components describing each alternative are not correlated between all the pairs of alternatives and that the variances of the random component are equal (Louviere et al., 2000, p. 15).

The assumption of IIA implies that the probability ratio of any two alternatives is unchanged by the addition of other alternatives (Ben-Akiva & Lerman, 1985; Greene, 2000; Sobel, 1980). In other words, the IIA property indicates that the relative probability of the alternative being selected does not depend on the availability of unavailable alternatives. For example, if driving alone is preferred over taking transit within the choice set {drive alone, transit}, introducing a third option such as carpooling or expanding the choice set to {drive alone, transit, carpooling} should not make transit preferable to driving alone. As travel decisions are commonly interrelated or jointly made with other decisions, the IIA assumption is the main limitation of MNL models. (Small & Winston, 1999).

As mentioned in the literature review, the travel mode choice decision is interrelated or jointly associated with mid-term decisions (such as car ownership) and long-term decisions (such as residential location choice or residential self-selection). As a result, the violation of the IIA property would result in incorrect and biased estimates in MNL models with an inaccurate prediction of mode share (Cervero & Duncan, 2002; Forinash & Koppelman, 1993; Louviere et al., 2000). If the IIA property is violated, the NL model is an alternative to the MNL model. However, the main limitation of NL models is that they cannot capture the direct and indirect effects between explanatory variables and outcome variables.

In traditional modeling techniques, highly correlated variables should be recognized and excluded from the model to avoid multicollinearity. Built environment factors are generally correlated with one another. In order to develop a model with correlations between independent variables, a different approach was implemented in the present study: a structural equation model. SEM is a powerful statistical technique for considering the direct and indirect effects of observed variables and incorporating the covariance or correlation between two variables as functions of the parameters of the model. However, developing an SE model requires a continuous, normally distributed outcome variable. Since mode choice and residential selection choice are either dichotomous measures, these variables do not meet the basic assumptions of linear relationships. According to Rabe-Hesketh, Skrondal, and Pickles (2004), GSEM is another approach that can be used to develop an SE model with discrete outcomes and include multilevel factors and even latent variables. Additionally, with GSEM, variables that do not fit the characteristics of a normal distribution can be estimated with generalized models. GSEM also provides a framework for developing structural models with both continuous and categorical outcome variables (B. Muthén, 1984; Rabe-Hesketh et al., 2004; StataCorp, 2017).

In this study, SEM is used to analyze daily VMT per household. To develop a multilevel discrete choice model with SEM techniques, GSEM was selected to examine the probability of individuals’ commute mode choices at the trip level.

Structural Equation Modeling (SEM)

SEM is a statistical technique also known as correlation structure analysis and covariance structure analysis. Several common multivariate techniques—including regression analysis, analysis of variance (ANOVA), multivariate analysis of variance (MANOVA), correlation analysis, and factor analysis—are incorporated in SEM (Bollen, 1989; Cheung, 2015). With SEM, multiple statistical techniques such as equations, path diagrams, and matrices can be integrated in a single framework. For example, factor analysis in psychology, path analysis in biology and sociology, and simultaneous equation models in economics can be combined using SEM (Bollen, 1989; Cheung, 2015; Goldberger & Duncan, 1973; Hoyle, 2012; Kaplan, 2000). SEM has been used in econometrics and social science for solving systems of interrelated regression equations.

SEM is rooted in the path-analysis diagrams introduced by Wright (1921) to specify relationships among observed variables. Wright's approach in the path-analysis diagrams developed the methodology for analyzing systems of structural equations and laid the foundation for SEM.

SEM represents the hybrid of two separate statistical techniques. The first technique is factor analysis, developed in the field of psychology and traced to the work of Galton (1869) and Pearson (Pearson and Lee, 1904) tackling the problem of inheritance of genetic traits. However, the common factor models can be credited to Spearman's (1904) work on the underlying structure of mental abilities (Kaplan, 2000). The second technique of SEM is simultaneous equation modeling, which was established primarily in econometrics but is originally rooted in the discipline of genetics (Kaplan, 2000). Economists such as Goldberger and Duncan (Goldberger, 1964, 1972; Goldberger & Duncan, 1973) proposed SE models with the purpose of investigating the interrelationships between variables (Cohen & Cohen, 1983).

Work by researchers such as Jöreskog (1967), Jöreskog and Lawley (1968), and Lawley and Maxwell (1962) led to the development of the maximum likelihood approach to factor analysis (Kaplan, 2000). The maximum likelihood approach allows researchers to examine the hypothesis that a specified number of factors are present to account for the intercorrelations among variables. Minimization of the maximum likelihood fitting function led directly to the likelihood ratio chi-square test of the hypothesis that a proposed model fits the data (Kaplan, 2000). A generalized least squares approach was later developed by Jöreskog and Goldberger (1971).

The calculation of SE models involves solving a set of equations—one for each “response” or “endogenous variable” in the model. Variables that are solely predictors of other variables are termed “influences” or “exogenous variables.” According to Kaplan (2000), the first SEM package on the market was developed by Jöreskog (1969, 1970, 1978), who integrated techniques such as equations and path diagrams into a single platform named LISREL (Jöreskog & Sörbom, 1993). Parallel with LISREL, a program called EQS was introduced by Bentler (1985, 1995). The development of applications such as LISREL and EQS popularized the implementation of SEM in various fields such as the social and behavioral sciences. Several recent powerful and user-friendly SEM packages, such as Mplus, AMOS, and STATA, have been developed and are available for researchers (Huber, 2013; L. Muthén & Muthén, 2012; Pallant, 2013).

Path analysis with endogenous and endogenous variables is a practical technique to investigate the interrelationship between land use and travel behavior. Various studies have used SE models to examine different outcomes of travel behavior such as VMT, trip frequencies, and vehicle ownership, addressing the endogenous causal effects between VMT and vehicle ownership (Bagley & Mokhtarian, 2002;

Brownstone & Golob, 2009; Dillon, 2017; Golob & Brownstone, 2005; Van Acker, Witlox, & Wee, 2007).

Generalized Structural Equation Modelling (GSEM)

The generalized linear model (GLM) framework of McCullaugh and Nelder (1989) has been applied commonly in biostatistics. GLM estimators include the normal (Gaussian) and inverse Gaussian for continuous data, Poisson and negative binomial for count data, Bernoulli for binary data (including logit and probit), and Gamma for duration data (Baum, 2016). Considering SEM and GLM techniques, GSEM is the combination of SEM's modeling capabilities with the GLM estimation framework to build models with latent variables as well as response variables that are not continuous. Whereas in SEM responses are continuous and models are linear regressions, in GSEM responses are continuous or binary, ordinal, count, or multinomial. In other words, GSEM techniques represent an extended model of SEM with the purpose of developing multilevel models with discrete outcomes (StataCorp, 2017). To develop a model with discrete outcomes, GSEM implements a variety of techniques such as logit, probit, ordinal logit, ordinal probit, and multinomial logit (StataCorp, 2017).

Modeling Framework

The modeling framework of this research includes two approaches: SEM and GSEM. First, an SE model with household-level travel survey data provides an opportunity to investigate continuous travel behavior outcomes such as VMT. As presented in Figure 12, this framework presents the effects of socioeconomic characteristics, built environment factors, and residential self-selection on the number of vehicles in household and VMT. In this figure, causal paths between two variables are illustrated by an arrow. A variable is endogenous when an arrow points to it. Exogenous variables are those with arrows only departing from them. In this framework, it is first assumed that the number of vehicles in households is affected by the built environment, socioeconomic characteristics of households, and their residential preferences. Second, it is assumed that VMT is directly influenced by the number of vehicles and is directly and indirectly affected by the built environment, socioeconomic characteristics, and residential preference.

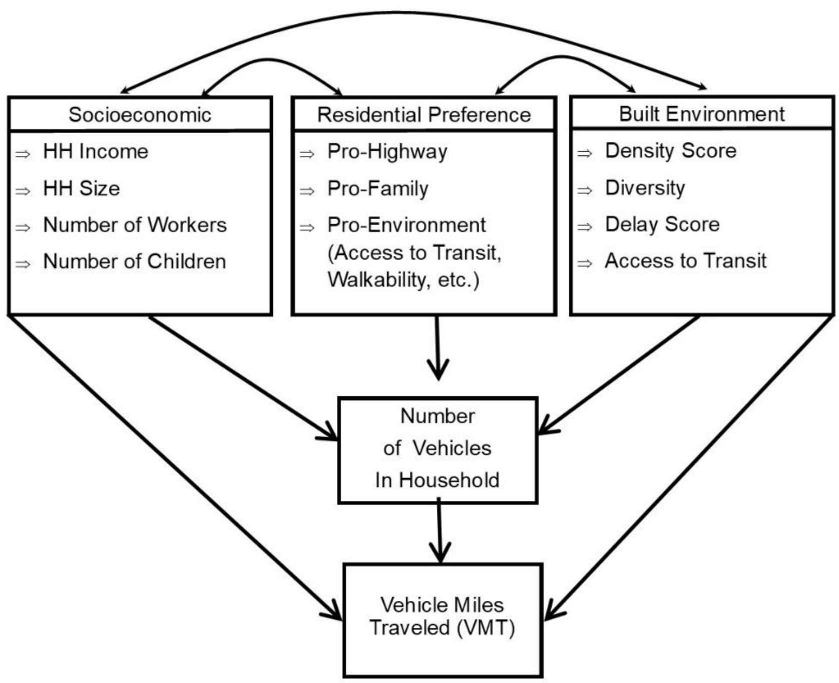

Figure 12. Conceptual Framework of VMT Model Using SEM

The second framework is based on the trip-level data that examines the probability of choosing modes of travel. The trip-level model was developed using GSEM with a logit-link function to handle discrete dependent variables. To explain factors that influence the choice of travel modes, a recursive GSEM with a logit link function was specified. This model includes explanatory variables addressing residential self-selection, built environment factors, and the socioeconomic characteristics of commuters. The outcome variables in this model include four modes of travel: drive-alone, carpooling (rideshare), transit (bus or train), and non-motorized (walking or biking). The conceptual model of this research is presented in Figure 13. All causal paths are directed towards the mode choices, representing a recursive model of mode choice behavior.

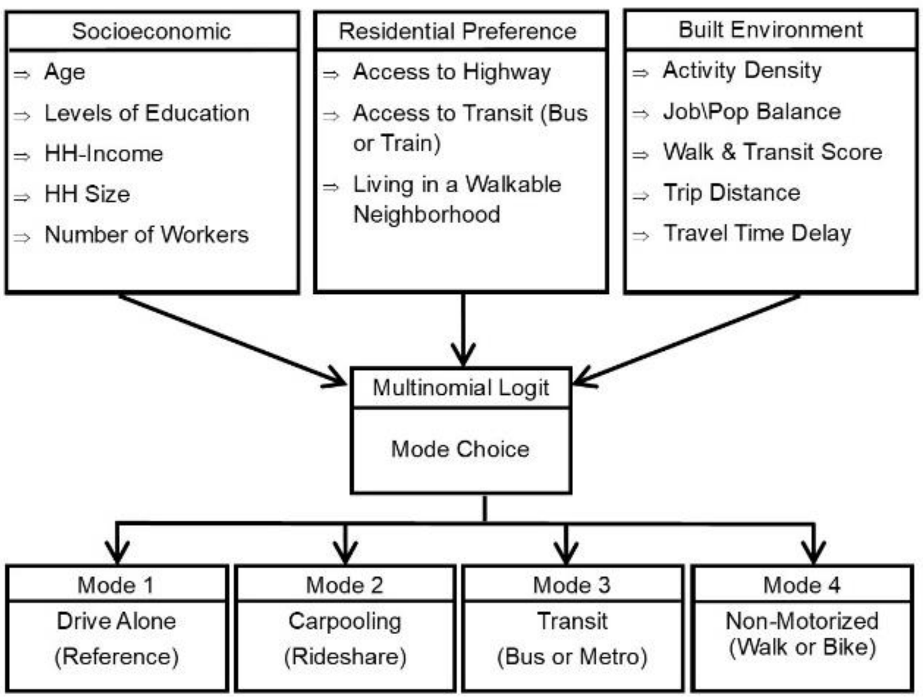

Figure 13. Conceptual Framework of Mode Choice Model Using GSEM

Data Integration

Data integration is a key aspect of this research methodology. In this study, datasets were gathered from several secondary sources including the U.S Census, the American Community Survey (ACS), the Longitudinal Employer-Household Dynamics (LEHD) program, the Transit-Oriented Development (TOD) database, the General Transit Feed Specification (GTFS), the National Historical Geographic Information System (NHGIS), Google Maps API, and Walk Score API. These datasets were collected, cleaned, and combined into a comprehensive dataset for further analysis.

To overcome the issue of aggregation bias, the present study incorporated disaggregated travel data from the Puget Sound Regional Council (PSRC). The PSRC Household Travel Survey data include disaggregated data with details regarding home, work, and trip end locations as gathered by GPS and other applications such as rSurvey and rMove. Figure 14 illustrates the details of data integration and presents the process of creating household-level and trip-level datasets.

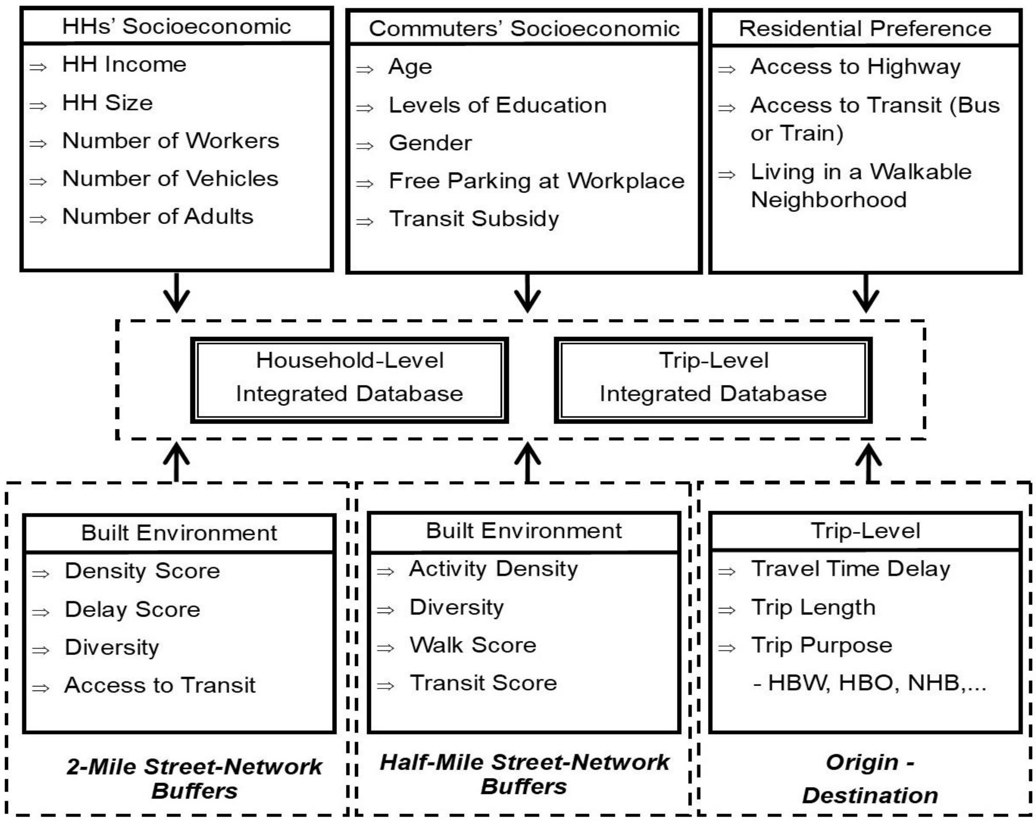

Figure 14. Data Integration Process

The next section presents the analysis of household travel survey data and explains the criteria applied to select the correct population sample from the PSRC travel survey and remove outliers from the household-level and trips-level datasets.

Household Travel Survey Data

The present study used the 2015 Puget Sound Regional Council (PSRC) Travel Behavior Survey to investigate the potential effects of traffic congestion on commuting mode choice. The survey was conducted in July and April of 2015 within two metropolitan areas in the state of Washington: the Seattle-Tacoma-Bellevue metropolitan area and the Bremerton-Silverdale metropolitan area.

The PSRC travel survey data were selected for two main reasons: First, it was recently completed household travel survey data at the time the present study was conducted. Second, it provides disaggregated travel survey data that includes the geocoded location of home, workplace, and all other trip-end locations. An advantage of a disaggregated travel survey over aggregated data is that the daily travel behavior of each household member can be identified and used for analysis.

In collaboration with the PSRC and with permission, restricted travel survey data with geocoded information were obtained for further analysis. These travel survey data include various groups such as low-income households, households without a vehicle, and households who frequently make transit or non-motorized trips within the Puget Sound region. The 2015 Travel survey data represent a 24-hour weekday-period activity diary that provides disaggregated information regarding households and individuals' characteristics and their trip patterns within the Puget Sound region.

The 2015 PSRC travel survey dataset includes completed data for 4,786 persons from 2,442 households with 18,712 records of trips for each household member. The advantage of using PSRC travel survey data is that the survey was completed in 2015 and recorded the exact geospatial location of trip origins and destinations using applications such as GPS, rMove, and rSurvey (Resource Systems Group (RSG), 2015). That is, trip origins and destinations can be precisely geocoded in GIS and combined with built environment datasets such as residential and employment locations. PSRC travel survey data include four separate datasets presenting vehicle information, individual surveys, household surveys, and daily (travel day) trip data. Appendix B provides a summary of the key questions in 2015 Travel Survey Program. The following section briefly summarizes each travel survey dataset.

Vehicle-Level Dataset

The vehicle-level dataset includes information about vehicle make, model, year, and fuel type. To compare with other datasets, the vehicle-level dataset is limited to a few questions about available vehicles in the household. In this study, the number of vehicles in the households were extracted from the vehicle-level dataset and joined with the household-level dataset.

Personal and Household-Level Datasets

PSRC travel survey data include the characteristics of individuals and households in separate datasets. Personal and household-level datasets contain several demographic factors which were selected to be appended to the sample. Also, these datasets were combined with other built environment variables to create the finalized sample dataset. The person-level file includes information for each household member age 5 and over in the sampled household. The person-level dataset covers factors addressing age, gender, license status, education, and employment type. The household-level dataset contains information about the sampled household, such as income, household size, number of adults, number of vehicles in the household, and home or work location. The household income question was measured on an ordinal scale. Also, the survey offered respondents the option to select “Prefer not to answer.” The person-level data also contain the main reasons that each person did not complete trips on a travel day.

Figure 15 shows the locations of the 2,442 households that participated in the 2015 Household Travel Survey.

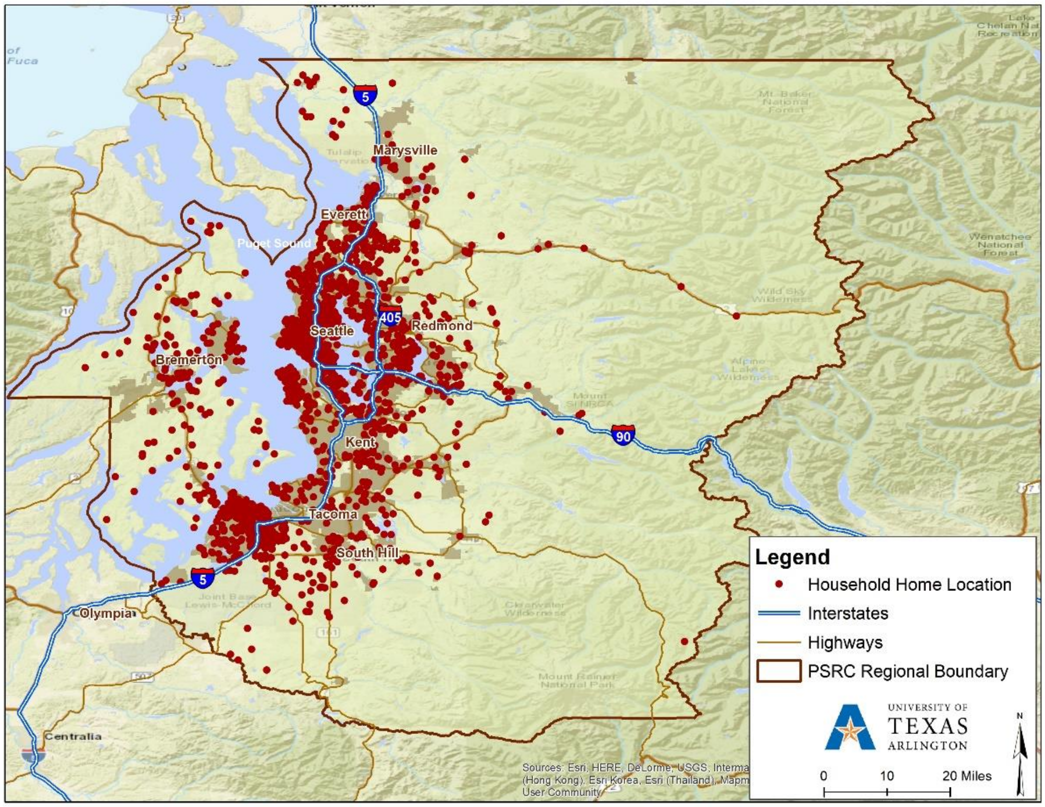

Figure 15. Households Home Locations in PSRC 2015 Travel Survey

Filters Applied to the Household-Level Data

Once the PSRC travel survey data were received, the datasets were cleaned, merged, and geocoded in ArcGIS and reorganized in Microsoft Access and Excel. The full dataset consists of 2,419 households within the PSRC area. Based on the purpose of the present research, four criteria were implemented for selecting the proper sample and removing outliers from the PSRC dataset:

- Selecting samples with reported trips during the weekdays. Households who did not report their trip are excluded from the sample.
- Selecting households with total travel miles fewer than 310 miles. According to the FHWA, households with more than 310 miles per day should be considered

outliers (U.S. Department of Transportation, Federal Highway Administration, 2009). Therefore, only households that reported VMTs of fewer than 310 miles were included in the sample.

- Selecting households with fewer than 20 trips per day. According to the FHWA, households with more than 20 trips per day should be considered outliers (U.S. Department of Transportation, Federal Highway Administration, 2009). Therefore, only households that reported fewer than 20 trips per day were included in the sample.

The final household-level dataset used to estimate the VMT model consists of 1,729 households. For this study, all continuous variables were transformed by taking natural logarithms, which reduces the impact of outliers and provides parameter estimates as elasticities. Table 5 through Table 7 provide summaries of demographics, their daily trips, and income groups from the selected samples at the household level.

Table 5. Descriptive Statistics of Household Demographic for the Selected Sample

SE Variables	N	Minimum	Maximum	Mean	Standard Deviation
HH Size	1,729	1.00	6.00	2.06	0.98
Number of Adults	1,729	1.00	5.00	1.78	0.64
Number of Children	1,729	0.00	4.00	0.28	0.65
Number of Workers	1,729	0.00	5.00	1.12	0.84
HH Vehicle Counts	1,729	1.00	10.00	1.79	0.95

Table 6. Descriptive Statistics of Households' Daily Trips at the Selected Sample

SE Variables	N	Minimum	Maximum	Mean	Standard Deviation
HH Number of Trips	1,729	1.00	20.00	7.93	4.38
HH Vehicle Miles Traveled	1,729	0.1	309.7	41.47	43.4

Table 7. Descriptive Statistics of Household Income at the Selected Sample

Income Group	Frequency	Percent	Cumulative Percent
Under $10,000	31	1.8	1.8
$10,000-$24,999	145	8.4	10.2
$25,000-$34,999	131	7.6	17.8
$35,000-$49,999	205	11.9	29.6
$50,000-$74,999	302	17.5	47.1
$75,000-$99,999	358	20.7	67.8
$100,000-$149,999	321	18.6	86.4
$150,000-$199,999	121	7.0	93.3
$200,000-$249,999	61	3.5	96.9
$250,000 or more	54	3.1	100.0
Total	1,729	100.0	

Trip-Level Dataset

In the trip-level dataset, each trip has a unique record ID representing household, person, and trip number. The trip-level dataset provides a summary of activities that were completed between origin and destination, including variables such as trip purpose, time of day, trip duration, and travel mode. Figure 16 presents an example of 18,712 trips with their origins and destinations.

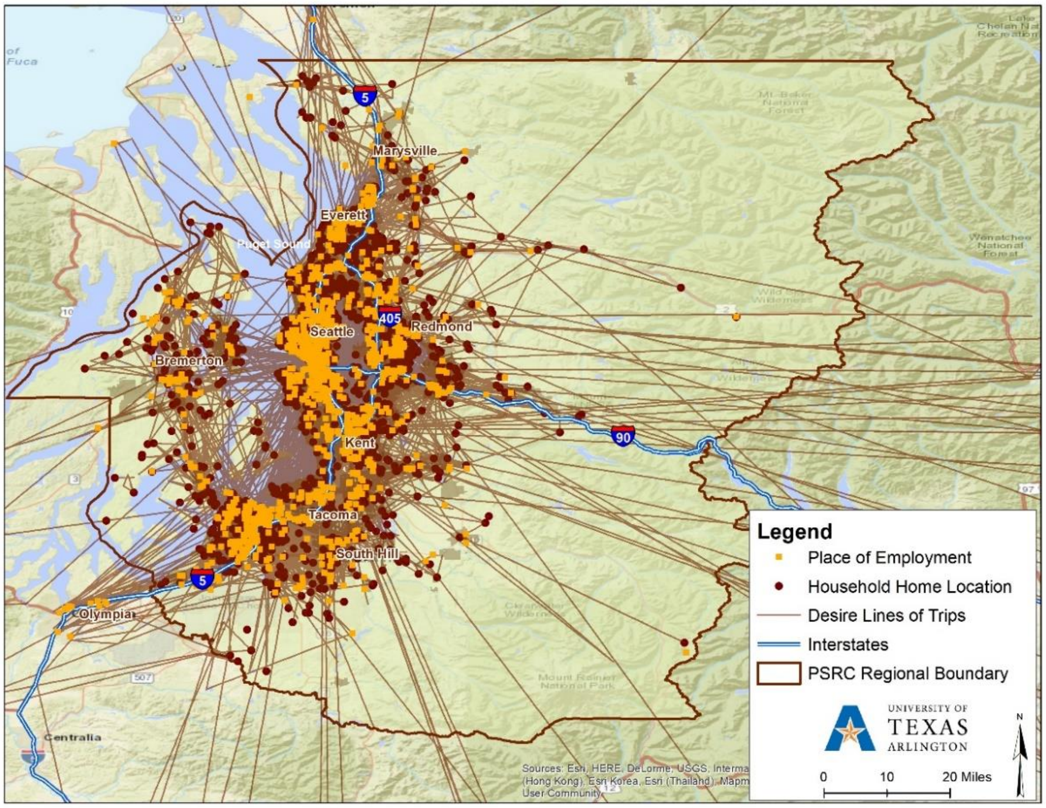

Figure 16. Desire Line of Trips in PSRC 2015 Travel Survey Data

Filters Applied to the Trip-Level Data

The full trip-level dataset consists of 18,712 trips covering a variety of travel modes taken by commuters 5 years of age or older. Based on the purpose of the mode choice model, four criteria were applied to select the proper sample and remove outliers from the PSRC dataset:

- Selecting reported mode of travel conducted during the weekdays. Commuters who did not report their mode of travel were excluded from the sample.
- Selecting typical travel modes by automobile, transit, and walk or bike. Other modes such as ferry and airplane were excluded.

- Selecting trips conducted by adults over 16 years of age. In the mode choice model, it is assumed that commuters are not dependent on others due to their age. As a result, reported trips for commuters younger than 16 years old were removed from the trip-level dataset.

The final trip-level dataset used to estimate the mode choice model consists of 14,619 trips conducted by 3,374 adults over 16 years old. The trip-level dataset includes four main modes of travel: driving alone, carpooling, transit, and non-motorized mode (walking\biking). Driving and carpooling were recognized as commuters using a private vehicle to drive to work or traveling in the same vehicle with other household members or other people who were not in the household. The transit mode was recognized as a person taking either a bus or train. Ultimately, walking and biking alternatives were combined into the non-motorized category. Table 8 presents the descriptive statistics of travel mode from the selected sample at the trip level.

Table 8. Descriptive Statistics of Travel Mode at the Trip-Level

Travel Modes	Frequency	Percent	Cumulative Percent
Drive Alone	6,355	43.5	43.5
Carpooling	3,892	26.6	70.1
Transit (Bus\Train)	1,225	8.4	78.5
Non-Motorized (Walk\Bike)	3,147	21.5	100.0
Total	14,619	100.0	

Table 9 through Table 11 provide summary statistics of trips and the socioeconomic characteristics of commuters, including level of education and income.

Table 9. Distribution of Trips by Demographic Factors of Commuters

SE Variables	Frequency	Percent	Cumulative Percent
Age			
16-17	143	1.0	1.0
18-24	536	3.7	4.6
25-34	2,505	17.1	21.8
35-44	2,582	17.7	39.4
45-54	2,396	16.4	55.8
55-64	3,008	20.6	76.4
65-74	2,452	16.8	93.2
75-84	845	5.8	99.0
85 or older	152	1.0	100.0
Total	14,619	100.0	
Gender			
Male	8,235	56.3	56.3
Female	6,384	43.7	100.0
Total	14,619	100.0	
Household Size			
1	3,677	25.2	25.2
2	6,457	44.2	69.3
3	2,198	15.0	84.4
4	1,673	11.4	95.8
5	454	3.1	98.9
6	122	.8	99.7
7	38	.3	100.0
Total	14,619	100.0	

Table 10. Distribution of Commuter Trips by Level of Education

Level of Education	Frequency	Percent	Cumulative Percent
Less than high school	325	2.2	3.2
High school graduate	917	6.3	8.5
Some college	2,165	14.8	23.3
Vocational/technical training	486	3.3	26.6
Associate degree	948	6.5	33.1
Bachelor’s degree	5,520	37.8	70.9
Graduate/post-graduate	4,258	29.1	100.0
Total	14,619	100.0	

Table 11. Distribution of Commuter Trips by Household Income Level

HH Income Level	Frequency	Percent	Cumulative Percent
Under $10,000	423	2.9	2.9
$10,000-$24,999	1,309	9.0	11.8
$25,000-$34,999	974	6.7	18.5
$35,000-$49,999	1,488	10.2	28.7
$50,000-$74,999	2,337	16.0	44.7
$75,000-$99,999	2,962	20.3	124.1
$100,000-$149,999	2,822	19.3	84.2
$150,000-$199,999	1,115	7.6	91.9
$200,000-$249,999	575	3.9	95.8
$250,000 or more	614	4.2	100.0
Total	14,619	100.0	

Residential Preference Data

The PSRC travel survey includes nine questions about factors influencing residential preferences and their importance when choosing one's current home location. These questions addressed the following factors: change in family size or marital/partner status; affordability; quality of schools (K-12); having a walkable neighborhood and being near local activities; having space and separation from others; being close to family or friends; being close to public transit; being close to the highway; and being within a 30-minute commute to work. The list of questions in the PSRC travel survey program are presented in Appendix B. The summary of participants' responses to these questions is presented in Table 12.

Table 12. Distribution of Households by Their Residential-Preference

Residential Preference	Frequency	Percent	Frequency	Percent	Frequency	Percent
A Change in Family Size or Marital/Partner Status			Having Space & Separation from Others		Having a Walkable Neighborhood	
Very Unimportant	486	28.1	153	8.8	106	6.1
Somewhat Unimportant	93	5.4	184	10.6	133	7.7
Neither or N/A	710	41.1	318	18.4	211	12.2
Somewhat Important	228	13.2	603	34.9	607	35.1
Very Important	212	12.3	471	27.2	672	38.9
Total	1,729	100.0	1,729	100.0	1,729	100.0
Quality of Schools			Being Close to Family or Friends		Being Close to Public Transit	
Very Unimportant	527	30.5	228	13.2	317	18.3
Somewhat Unimportant	114	6.6	168	9.7	215	12.4
Neither or N/A	438	25.3	399	23.1	370	21.4
Somewhat Important	290	16.8	591	34.2	473	27.4
Very Important	360	20.8	343	19.8	354	20.5
Total	1,729	100.0	1,729	100.0	1,729	100.0
Affordability			Within a 30-Minute Commute to Work		Being Close to the Highway	
Very Unimportant	77	4.5	192	11.1	190	11.0
Somewhat Unimportant	61	3.5	114	6.6	260	15.0
Neither or N/A	116	6.7	298	17.2	378	21.9
Somewhat Important	481	27.8	376	21.7	674	39.0
Very Important	994	57.5	749	43.3	227	13.1
Total	1,729	100.0	1,729	100.0	1,729	100.0

Residential Preference at Household-Level Data

In the household VMT model, residential preferences are summarized in three categories: pro-environment, pro-family, and pro-highway. Based on the input of six self-reported residential preferences, two latent factors—pro-environment and pro-family—were extracted using principal component analysis (PCA). As shown in Table 13, the pro-environment factor was constructed based on three variables: walkability, transit accessibility, and distance to workplace. The pro-family factor is a combination of residential preferences based on school quality, changes in household status, and proximity to family or friends. In addition to these two factors, the pro-highway factor was directly extracted based on the household's response to the question of how highway access affected their current home location selection.

The adequacy of pro-environment and pro-family variables were examined using Bartlett's test of sphericity. Bartlett's test rejected the null hypothesis (X^2 = 964.3, *df* = 15), indicating that there is a high level of intercorrelation among the variables, allowing us to reduce the number of variables. Multicollinearity was investigated using the Kaiser-Meyer-Olkin (KMO) statistic to determine sampling adequacy. The KMO statistic ranges from 0 to 1, with small values indicating that the variables do not have enough in common. The analysis resulted in a KMO value of 0.671, which is greater than the threshold of 0.6. Additionally, the reliability of the PCA was investigated with Cronbach's alpha test, which has a maximum value of 1. The resulting Cronbach's alpha value of 0.653 is greater than the threshold of 0.6 (Sangkapichai & Saphores, 2009). To simplify the interpretation, the residential selection variables were normalized (to be between 0 and 1, where 1 represents stronger preferences.

Table 13. Loading Factors

Reasons for Residential Selection	Component	
	1: pro-environment	2: pro-family
Having a Walkable Neighborhood	.831	
Being Close to Public Transit	.754	
Within a 30-Minute Commute to Work	.650	
Quality of Schools		.783
A Change in Family Size or Marital/Partner Status		.746
Being Close to Family or Friends		.481
Note: Extraction Method: Principal Component Analysis; Rotation Method: Promax with Kaiser Normalization; Rotation converged in three iterations.		

The normalization was completed using Equation 1.

$$\mathrm{zi} = \frac{xi - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Residential Preference at the Trip Level

The data for residential preference include three residential factors directly related to the mode of travel: neighborhood walkability, proximity to public transit, and proximity to highways. Therefore, the effects these factors are considered in the mode choice model. Table 14 presents residential preferences at the trip level.

Table 14. Distribution of Trips Based on Commuters' Residential Preferences

Residential Preference	Frequency	Percent	Cumulative %
Having a Walkable Neighborhood			
Very Unimportant	839	5.7	5.7
Somewhat Unimportant	943	6.5	12.2
Neither or N/A	1,504	10.3	22.5
Somewhat Important	4,736	32.4	54.9
Very Important	6,597	45.1	100.0
Total	14,619	100.0	

Table 14—Continued

Residential Preference	Frequency	Percent	Cumulative %
Being Close to Public Transit			
Very Unimportant	2,311	15.8	15.8
Somewhat Unimportant	1,530	10.5	26.3
Neither or N/A	2,695	18.4	44.7
Somewhat Important	3,788	25.9	70.6
Very Important	4,295	29.4	100.0
Total	14,619	100.0	
Being Close to the Highway			
Very Unimportant	2,092	14.3	14.3
Somewhat Unimportant	2,363	16.2	30.5
Neither or N/A	3,344	22.9	53.3
Somewhat Important	5,111	35.0	88.3
Very Important	1,709	11.7	100.0
Total	14,619	100.0	

Trip Purpose Data

At the trip level, trip purposes are classified based on five major groups: Home-Based Work (HBW), Home-Based Other trips (HBO), Non-Home-Based (NHB), Shopping trips (SHOP), and Social and Recreational trips (SOCREC). Home-based trips include trips in which either the origin or destination is the respondent's home.

For all SHOP trips, one end had a trip purpose of grocery shopping or other shopping such as a mall or pet store. SOCREC trips represent trips where one end of the trip involves going to a restaurant, a gym, a social or recreational event, or going to a religious, community, or volunteer activity. HBO trips include a trip in which one end is home and the other end is none of the above categories. Other trips in which the home is not the origin or destination are classified as NHB. Table 15 presents the percent distribution of trip purposes. As expected, the distribution varies by trip purpose. HBW, HBO, and SOCREC trips comprise 17.1, 18.2, and 19.8 percent of trips, respectively, whereas only 12.4 percent of trips are SHOP trips. NHB trips account for 32.13 percent of person trips in the selected sample from the PSRC travel survey.

Table 15. Trip Purposes in Trip-Level Data

Trip Purpose	Frequency	Percent
Home-based Work (HBW)	2,505	17.13
Home-based Other (HBO)	2,663	18.21
Non-Home Based (NHB)	4,733	32.37
Shopping (SHOP)	1,823	12.47
Social and Recreational (SOCREC)	2,895	19.80
Total	14,619	100.0

Built Environment Data

Characteristics of the built environment around households' home and work locations were derived from several secondary sources, including U.S. Census data, the ACS, the Highway Performance Monitoring System (HPMS), the GTFS, the NHGIS, and the LEHD. The built environment dataset includes information about job/population balance, population density, employment density, activity density, road density, and access to public transit. Using ArcGIS software, built environment datasets were summarized around each persons's home location, workplace, and other trip-end locations. Additional information related to walkability and transit services was obtained from Walk Score and Transit Score APIs. These data provide information about the number of transit routes as well as transit score and walk score near home and work locations. Built environment data were placed in two datasets, as explained below.

Figure 17 presents an example of using the ArcGIS network analyst tool to generate 2-mile and half-mile network buffers around home, work, and trip-end locations.

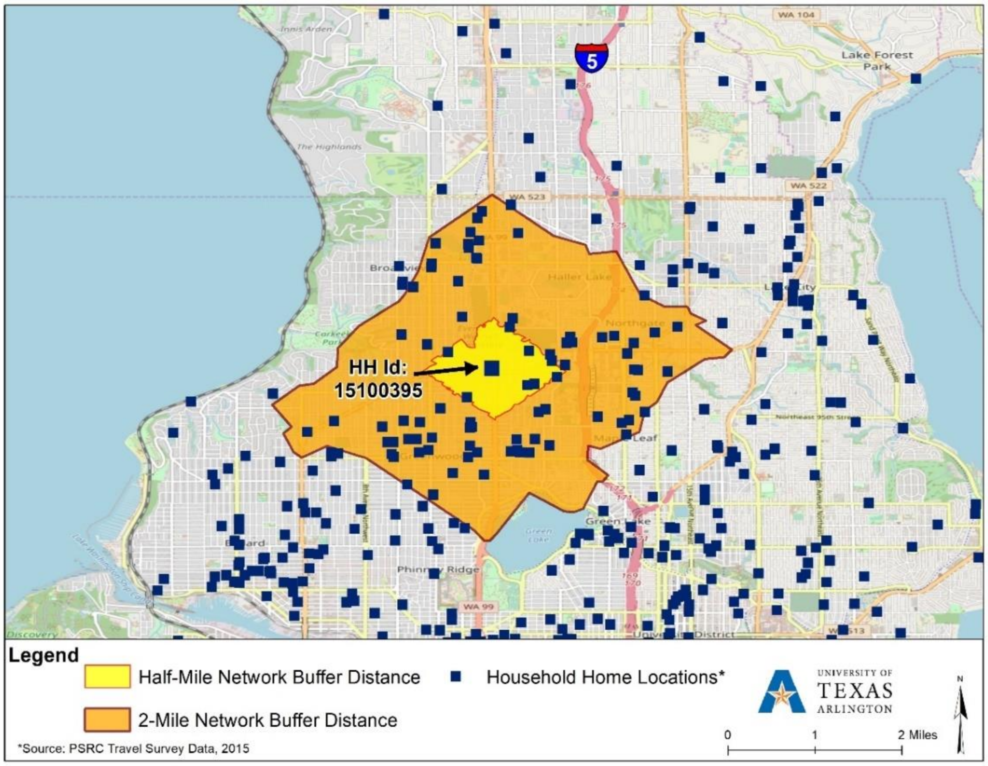

Figure 17. Street-Network Buffers Using ArcGIS Network Analyst

Built Environment Data Near Home Locations

For the household VMT model, built environment data were collected at 2-mile network buffers around households' home locations. It is necessary to note that previous studies commonly considered a half-mile buffer to summarize built environment data. However, with a focus on traffic congestion analysis, a previous study by Sardari, Hamidi, and Pouladi (2018) found that 2- to 5-mile buffers are the optimal thresholds to examine traffic congestion and its effects on VMT. This threshold is related to the fact that traffic congestion mostly occurs on highways, major arterials, and main roads. To be consistent with the level of congestion data, built environment data were extracted within 2-mile network buffers.

Concerning density relative to unprotected areas, protected areas within the network buffers were calculated using the Protected Areas Database of the United States (PAD-US) (U.S. Geological Survey, Gap Analysis Program (GAP), 2016). Using this database, unprotected land was calculated by subtracting protected land from total land within network buffers. The road density and intersection density were calculated based on the public release of HPMS geospatial data in the shapefile format. Equations 2 through 7 present the formulas for calculating each built environment factor within a 2-mile network buffer.

$$\text{Job Density} = \frac{\text{Total Job}}{\text{Unprotected Land (acre)}} \tag{2}$$

$$\text{Population Density} = \frac{\text{Total Population}}{\text{Unprotected Land (acre)}} \tag{3}$$

$$\text{Activity Density} = \frac{\text{Employment + Housing Units}}{\text{Unprotected Land (acre)}} \tag{4}$$

$$\text{Road Density} = \frac{\text{Total Lane Miles of Roads}}{\text{Unprotected Land (acre)}} \tag{5}$$

$$\text{Intersection Density} = \frac{\text{Number of Intersections}}{\text{Unprotected Land (acre)}} \tag{6}$$

$$\text{Job/Population Balance} = 1 - \text{ ABS } \left(\frac{(\text{Ji}-\text{Jp}*\text{Pi})}{(\text{Ji}+\text{JP}*\text{Pi })}\right) \tag{7}$$

Where:
i= Household home location number
J= Total jobs near home location
P= Total population near home location
JP= Average Job per person in the Puget Sound region

The job/population balance ratio can range from 0 to 1. A value of 0 represents areas with only jobs or residents within the 2-mile buffer, but not both. A value of 1 indicates areas with the same ratio of jobs-to-residents within the 2-mile buffer as within the metropolitan area as a whole. Table 16 provides a summary statistics of built environment data within a 2-mile network buffer from home locations.

Table 16. Summary Statistics of Built Environment Data Near Home Location

Built Environment Attributes	N	Minimum	Maximum	Mean	Std. Deviation	Source
Job Density (acre)	1,729	0.00	35.79	4.99	7.81	LEHD
Population Density (acre)	1,729	0.05	18.52	6.48	3.28	Census
Activity Density (job + housing units /acre)	1,729	0.06	45.74	8.11	9.57	Census
Road Density (sq. mile)	1,729	.80	41.9	20.3	9.0	HPMS
Intersection Density (sq. mile)	1,729	0.1	98.8	27.3	26.4	HPMS
Job Population Balance	1,729	0.06	.98	0.65	0.23	Census - LEHD
Number of Transit Stations	1,729	0.00	624	131.3	22.28	GTFS

Principal Component Analysis for Density Score

As the density factors of the built environment are highly correlated, four density factors were combined into one density score. Using PCA, a density score was extracted based on four built environment factors representing population density, employment density, road density, and intersection density. From the loadings, it is noted that the component of these four variables accounts for 92 percent of the total variation, representing a density factor. The results indicate a KMO equal to .798, which indicates a good measure of adequacy. The reliability of the density factor was investigated by Cronbach's alpha test, resulting in a significant value of .89, which exceeds the threshold of 0.6.

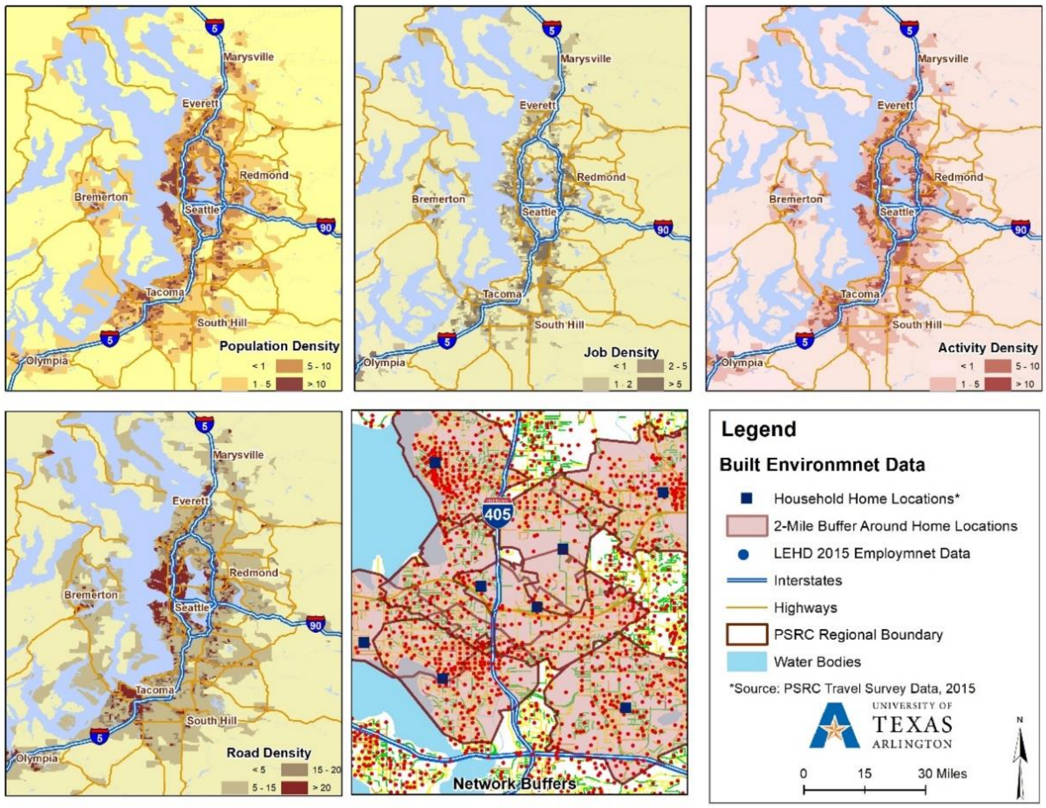

Figure 18. Example of Built Environment Data Near Home Locations

Built Environment Data at the Trip Level

For the mode choice trip-level model, built environment data were extracted within 0.5-mile network buffers around the origin and destination of trips. This threshold is based on a previous study presented by Cervero and Ewing (2010). In their study, they found that 0.5 miles is an appropriate threshold for mode choice and accessibility analysis.

According to Cervero (2002), mode choice is associated with the characteristics of points A (origins) and B (destinations). Therefore, it is necessary to consider the potential effects of built environment factors around both trip origins and destinations. Table 17 provides summary statistics of built environment data near the origins and destinations of trips. The formulas of activity density and job/population balance are presented in Equation 4 and 7, respectively. The Walk Score and Transit Score were obtained from Walk Score API, and trip distances are directly reported in the PSRC household travel survey dataset.

Table 17. Summary Statistics of Built Environment Data Near Origins and Destinations

Built Environment Attributes	Location	*N*	Minimum	Maximum	Mean	Standard Deviation
Activity Density (per acre)	Origin	14,619	0.1	188.9	16.48	33.05
	Destination	14,619	0.1	277.9	16.51	33.31
Job/Population Balance	Origin	14,619	0.0	1.00	0.48	0.29
	Destination	14,619	0.0	1.00	0.48	0.29
Walk Score	Origin	14,619	0.0	100.0	62.11	28.90
	Destination	14,619	0.0	100.0	62.07	28.90
Transit Score	Origin	14,619	0.0	100.0	43.99	29.22
	Destination	14,619	0.0	100.0	43.96	29.21
Trip Distance (miles)	O-D	14,619	0.0	110.20	5.21	8.00

Figure 19 and Figure 20 present the activity density and job/population balance, respectively, near the origins and destinations of trips. As shown, higher activity densities and job/population balances are located at downtown Settle, Redmond, Kent, and Tacoma.

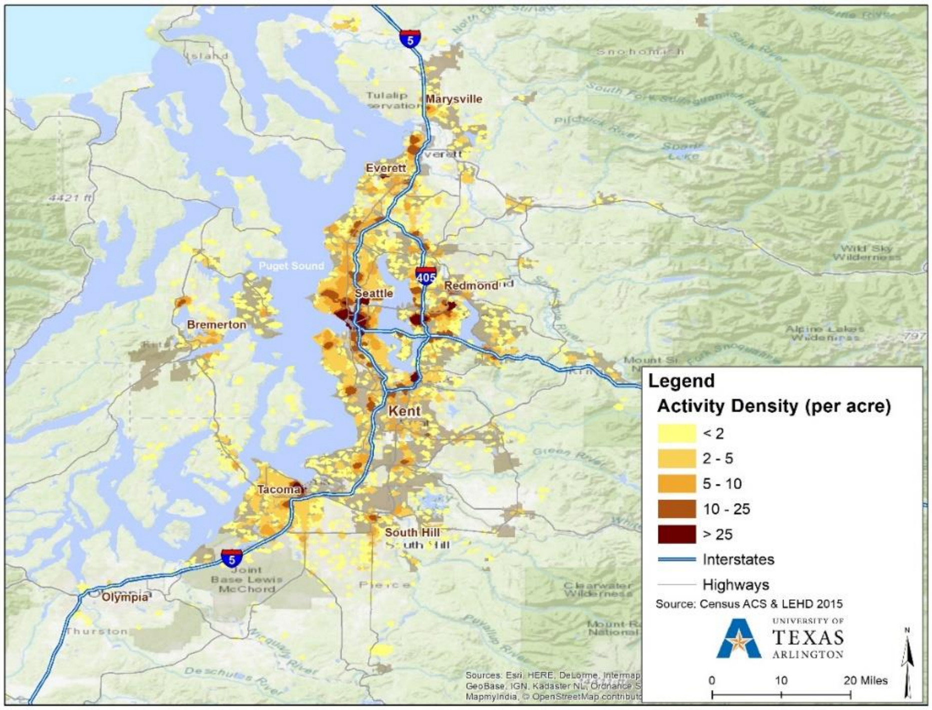

Figure 19. Activity Density Near Origins and Destinations of Trips

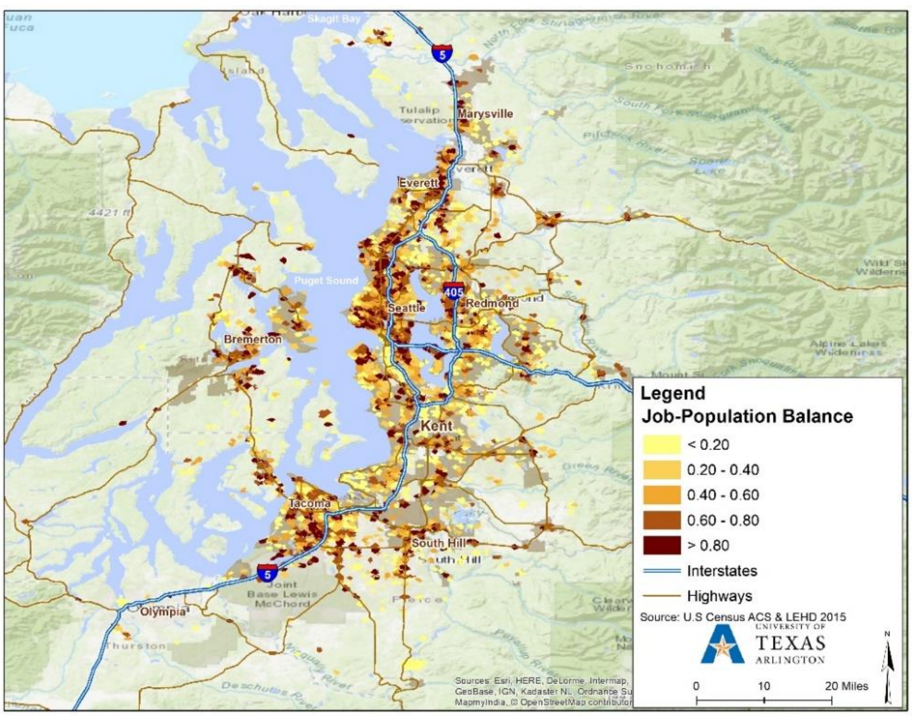

Figure 20. Job/Population Balance Near Origins and Destinations of Trips

Walk Score and Transit Score Near Origins and Destinations

Walk Score® and Transit Score® data were used to measure the level of walkability and access to public transit near the origins and destinations of trips. For each location, the Walk Score investigates the walking routes to nearby amenities within a 5-minute walk, or 0.25 miles. Using a distance decay function, the Walk Score quantifies pedestrian friendliness by exploring population density and transportation network metrics such as intersection density and block length. The Walk Score is based on a variety of data sources including the U.S. Census, Google, Education.com, Open Street Map, and Localeze.[1] The Walk Score methodology was developed by the Walk Score Advisory Board and has been validated by academic researchers (Duncan, Aldstadt, Whalen, Melly, & Gortmaker, 2011). In a study by Duncan et al. (2011), Walk Score data were validated within four U.S. metropolitan areas, and it was determined that the Walk Score is a valid indicator of examining neighborhood walkability in multiple geographic locations and at different spatial scales.

The Transit Score is another measure that quantifies access to public transit and indicates how well a location is served by public transit. The Transit Score is based on GTFS data released in a standard format by public transit agencies. The Transit Score is estimated based on transit frequency, type of transit (bus or rail), and distance to the nearest stop on the route.[2] Table 18 summarizes the Walk Score and Transit Score classifications, ranked from 0 to 100.

[1] See www.walkscore.com/methodology.shtml
[2] See www.walkscore.com/transit-score-methodology.shtml

Table 18. Classification of Walk Score and Transit Scores

Walk Score®	Description	Transit Score®	Description
90–100	Walker's Paradise; Daily errands do not require a car.	90–100	Rider's Paradise; World-class public transportation.
70–89	Very Walkable; Most errands can be accomplished on foot.	70–89	Excellent Transit; Transit is convenient for most trips.
50–69	Somewhat Walkable; Some errands can be accomplished on foot.	50–69	Good Transit; Many nearby transit options.
25–49	Car-Dependent; Most errands require a car.	25–49	Some Transit; A few nearby transit options.
0–24	Car-Dependent; Almost all errands require a car.	0–24	Minimal Transit; 0 Value presents No Nearby Transit

Source: WalkScore.com

The Walk Score website provides an API tool that allows users to input their address and receive the Walk Score and Transit Score assigned to that location. In this study, the Walk Score and Transit Score of trip origins and destination were obtained by adding the longitude and latitude of trip origins and destinations into the API, with scores then returned by the API calls. Appendix C presents the requirements for the API tool. Table 19 and Table 20 provide summary statistics of the Walk Score and Transit Score, respectively, near the origins and destinations of trips.

Table 19. Summary Statistics of Walk Score Near Origin and Destination

Walkability Score	Origin		Destination	
	Frequency	Percent	Frequency	Percent
Car-Dependent	4,586	31.4	4,597	31.4
Somewhat Walkable	3,296	22.5	3,297	22.6
Very Walkable	3,535	24.2	3,534	24.2
Walker's Paradise	3,202	21.9	3,191	21.8
Total	14,619	100.0	14,619	100.0

Table 20. Summary Statistics of Transit Score Near Origin and Destination

Transit Score	Origin		Destination	
	Frequency	Percent	Frequency	Percent
No Nearby Transit	2,358	16.1	2,361	16.2
Minimal Transit	1,193	8.2	1,197	8.2
Some Transit	5,074	34.7	5,072	34.7
Good Transit	3,371	23.1	3,366	23.0
Excellent Transit	1,129	7.7	1,137	7.8
Rider's Paradise	1,494	10.2	1,486	10.2
Total	14,619	100.0	14,619	100.0

Figure 21 and Figure 22 show the spatial patterns of the Walk Score and Transit Score, respectively, near the origins and destinations of trips.

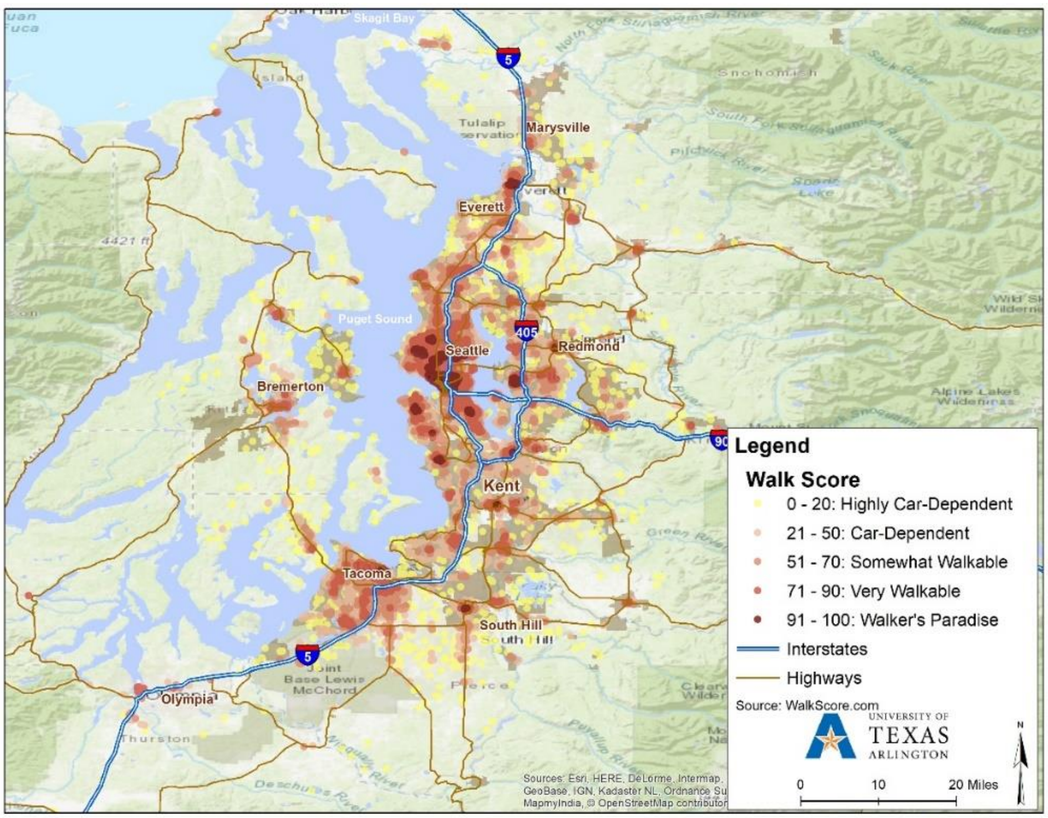

Figure 21. Walk Score Near Origins and Destinations of Trips

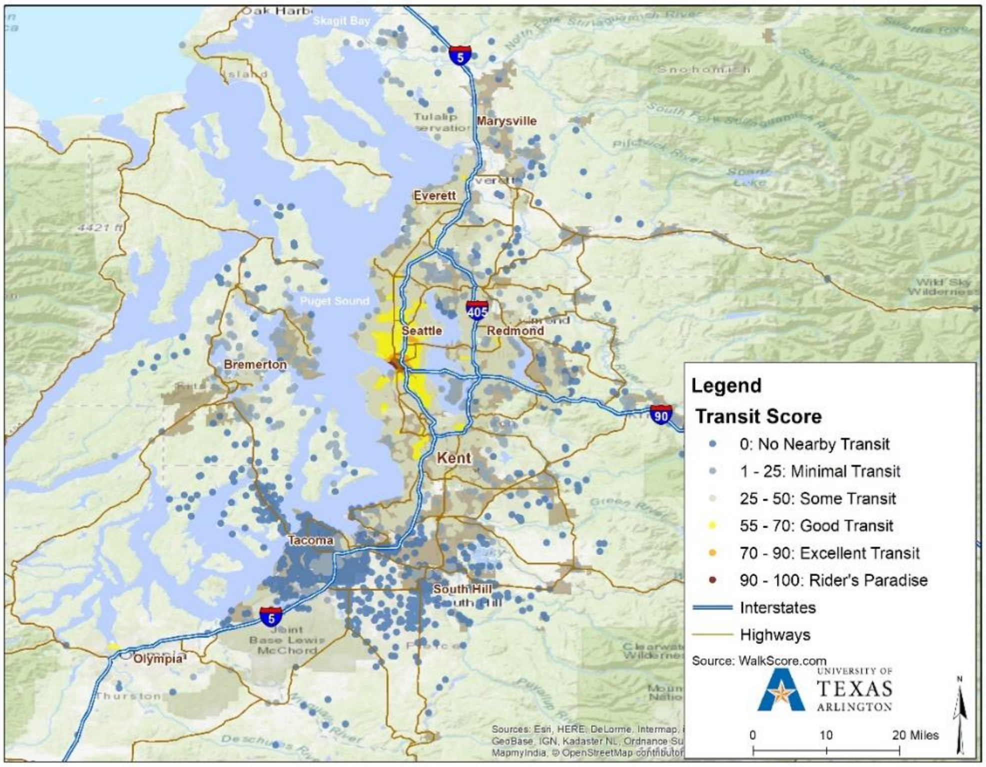

Figure 22. Transit Score Near Origins and Destinations of Trips

Traffic Congestion Data

Developing a time-related mobility measure is a practical approach to examining the effects of congestion on mode choice. As mentioned in the literature review, developing a time-related mobility measure requires a massive amount of traffic data including the details of actual travel times and speeds during peak and off-peak hours. As mentioned in the previous chapter, travel time delay is the recommended time-related mobility measure and can be calculated based on peak and off-peak travel time data.

This study has the advantage of analyzing travel time data from peak and off-peak periods extracted from the Google Maps API. Appendix D presents the requirements for the Google Maps API. In this study, a delay score was calculated as the primary indicator of traffic congestion. It is important to note that Google travel time data are based on historical data that are not allocated to a specific year. Google's traffic model returns driving duration considering time spent in traffic, which is predicted based on historical averages. Therefore, integrating these historical data into the household travel survey dataset provides an ideal travel time indicator.

The following section describes how congestion was quantified in two ways to be used in the VMT model and mode choice model.

Travel Time Delay Score

For the VMT model, traffic congestion was measured by a travel time delay score, which was calculated using time-related data from the Google Maps API. The Google Maps Distance Matrix provides the opportunity to obtain travel time data between each origin and destination by time of day. This information derived from Google Maps provides a significant resource for measuring small-scale traffic congestion.
Google's Terms of Service allow users or developers to implement data for limited amounts of content if it is temporarily and securely used in the application (Google LLC, 2018). In this application, Google travel time data for a distance of 2 miles around home locations were temporarily obtained for peak and off-peak hours during weekdays. Then, the delay score around each home location was calculated based on average travel time during peak and off-peak hours within the 2-mile network buffer. Once off-peak and peak travel times within 2 miles were gathered, the delay score was calculated. Equation 8 presents the formula for calculating the delay score.

$$\text{Delay Score} = \left(1 - \frac{\text{Average Free Flow Travel Time (Weekdays)}}{\text{Average Travel Time During Peak Periods (Weekdays)}}\right) * 100 \qquad (8)$$

Table 21 presents the descriptive statistics of the average travel time delay within the 2-mile network buffer.

Table 21. Descriptive Statistics of Travel Time Delay

Variable	Minimum	Maximum	Mean	Standard Deviation
Average travel time delay within 2-mile network buffer (Minutes)	0.05	14.45	3.43	3.27

Figure 23 illustrates the neighborhoods with higher levels of travel time delays, as calculated within a 2-mile network buffer. Higher levels of traffic congestion are located at downtown Seattle, Bellevue, and Redmond.

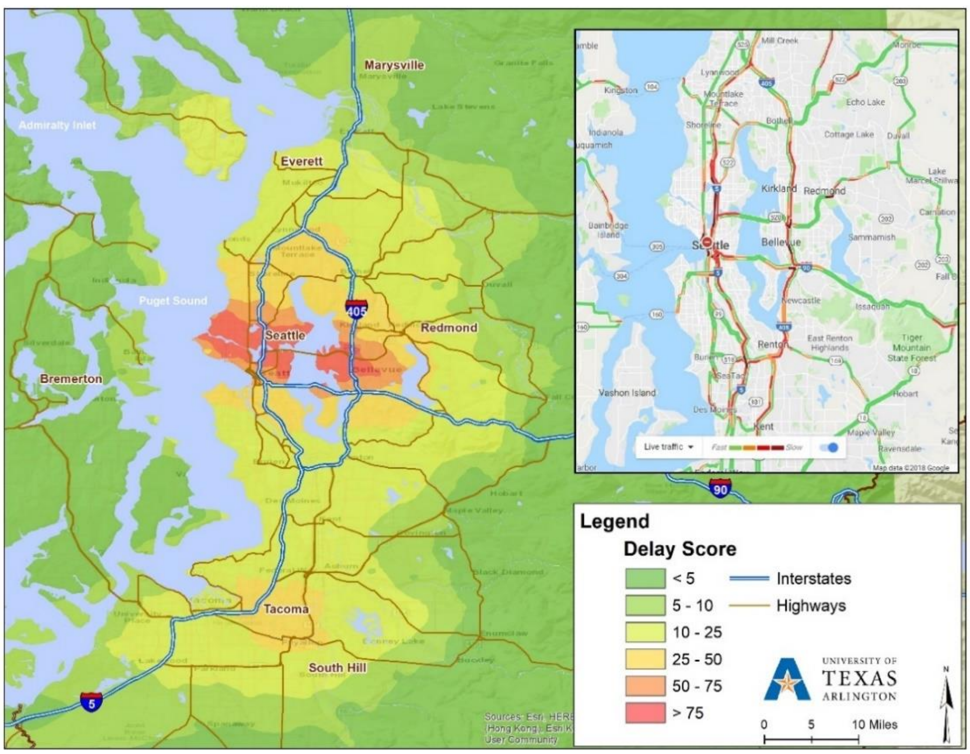

Figure 23. Delay Score Within 2 Miles from Home Locations

Average Travel Time Delay Between Origin and Destination

At the trip level for the mode choice model, traffic congestion was quantified based on the extra time required to conduct a trip during peak hours. As the Google Maps API provides travel times over the selected period between every point pair within a region, travel time delay was calculated to examine the travel time delay when a particular trip took place. For this study, the Google Maps API was used to calculate travel time between individuals' trips origins and destinations based on the time of the trip. Once travel time by time of day was gathered, travel time delay was quantified as a time-related mobility measure addressing the average travel time during peak and off-peak periods on weekdays.

Figure 24 presents travel time delay in minutes between the origins and destinations of trips. The travel time delay is a continuous measure that examines traffic congestion. This continuous congestion measure has an advantage over discrete factors because it can be easily measured, and it has a straightforward interpretation. Table 22 summarizes the descriptive statistics of total delay at the trip level. Figure 24 illustrates the desire lines of trips and their average travel time delays in minutes.

Table 22. Descriptive Statistics of Total Delay at Trip-Level

Factor	N	Minimum	Maximum	Mean	Standard Deviation
Travel Time Delay between Origin and Destination of Trips	14,619	.00	38.56	5.21	5.07

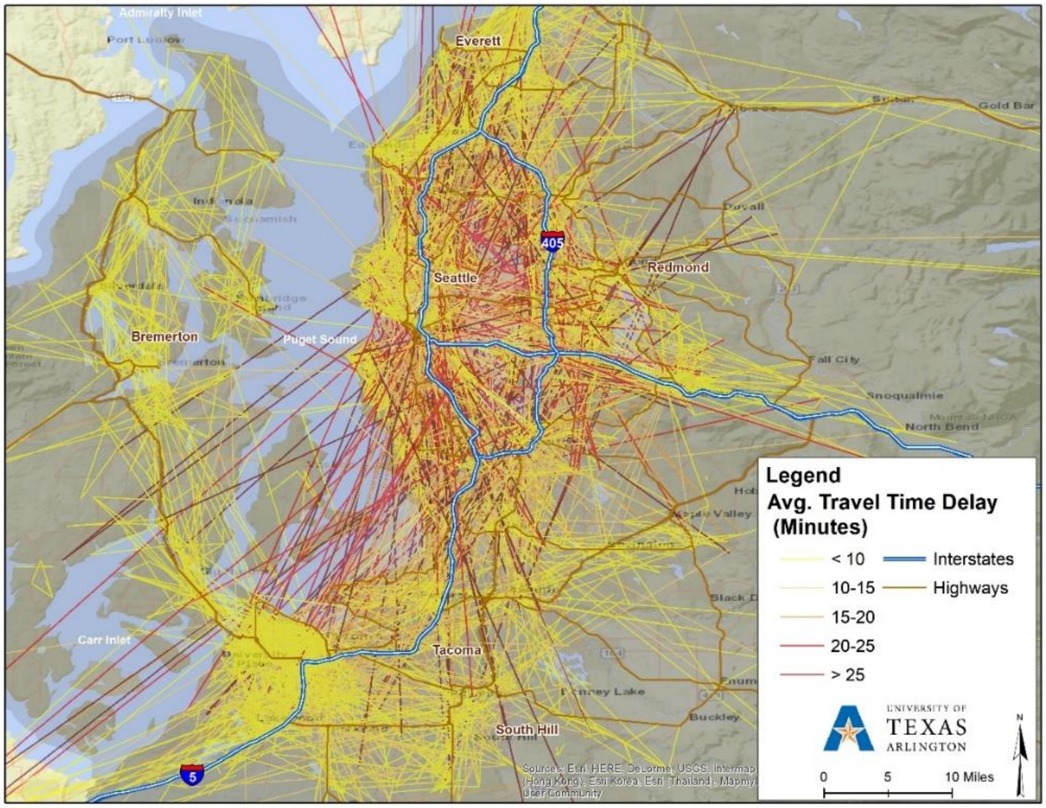

Figure 24. Average Travel Time Delay in Minutes at Trip-Level

Summary

This chapter summarized the present study's statistical approaches and data integration. Subsequently, this chapter provided summary statistics of the selected sample population from the household travel survey data. Using ArcGIS for data construction, this chapter explained the process of quantifying traffic congestion and measuring built environment factors such as density and job/population density.

The next chapter explains the explanatory variables used via SEM and GSEM, model specifications, model fit, and the results of the VMT and mode choice models.

Chapter 5

Empirical Analysis

This chapter reviews the results of two models that adopted comprehensive frameworks for the present investigation and included congestion and self-selection factors in addition to the built environment and socioeconomic variables. First, the chapter discusses the VMT model, with its explanatory variables analyzed via SEM. Then, the interpretations of estimated coefficients are explained in detail. Using SPSS AMOS software, model fit statistics and maximum likelihood estimates of the model parameters are provided in this section.

The next section introduces the mode choice model and the process of developing and validating GSEM in STATA. Also, this phase summarizes a list of variables implemented via GSEM followed by the results of probabilities for selecting each mode of travel. This section comprises five separate models, building from a simple model with only demographic factors to the full model with all variables. The first model includes only socioeconomic characteristics. In the second model, variables related to residential preference are added to the first model. The third model comprises the second model and trip purpose variables. The fourth model includes the third model plus the built environment factor, transit score, and walk score. By using walk score and transit score data, the characteristics of the built environment and transit service at residential and employment locations are also examined in the model. The fifth model, the full model, contains the fourth model plus the travel time delay variable. The effects of adding variables to the model were analyzed using the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). The results of these models are explained in the corresponding sections of this chapter.

VMT Model Using SEM

This phase implements SEM—a statistical technique also known as correlation structure analysis and covariance structure analysis—to analyze VMT per household. As mentioned in Chapter 3, several common multivariate techniques such as regression analysis, analysis of variance (ANOVA), multivariate analysis of variance (MANOVA), correlation analysis, and factor analysis can be classified as special models of SEM (Bollen, 1989; Kaplan, 2000). SEM is a powerful statistical technique for considering the direct and indirect effects of observed variables and calculating the covariance or correlation between two variables as functions of the parameters of the model. One advantage of SEM is that multiple statistical tools such as equations, path diagrams, and matrices can be integrated into a single framework that is appropriate for analyzing built environment factors, which are generally correlated with one another. Since excluding correlated variables raises questions about analytical bias, SEM provides a practical technique to develop a model that includes the correlations between explanatory variables.

Following the theories developed and used in previous studies, this study considers factors across three main categories:

(1) socioeconomic characteristics of households,

(2) built environment features of residential locations and workplaces, and

(3) household preferences for residential locations.

It is hypothesized that when controlling for socioeconomic and built environment factors, higher travel time delay will mitigate daily household VMT.

VMT Model Variables

VMT is associated with a variety of variables such as socioeconomic, residential self-section, and built environment factors. As mentioned in the literature review, the influences of socioeconomic factors on travel behavior have been discussed in theories such as the Theory of Planned Behavior (Fishbein & Ajzen, 1975) and tested in previous studies (Bento et al., 2005; Ewing & Cervero, 2010a; Hanson & Hanson, 1981; T. Lin, Wang, & Guan, 2017; Tilahun & Fan, 2014). For instance, studies have concluded that VMT is positively and significantly correlated with household size, number of children, and the number of working adults (Bento et al., 2005; Brownstone & Golob, 2009; Diao & Ferreira Jr, 2014). The life cycle has a significant impact on travel behavior as well. Brownstone and Golob (2009) presented evidence that retired two-person households and households with older children have higher annual VMT. Income is another socioeconomic factor that influences travel behavior. Tilahun and Fan (2014) presented that public transit is the main mode of transportation for low-income workers who do not have access to private cars. Also, Bento et al. (2005) presented that income is positively associated with VMT and higher income groups had higher annual VMT.

Based on the relevant theories, previous studies, and the model fit, the final VMT model includes the following socioeconomic factors: household size; number of household workers; number of children in the household; household income; and living in rental homes, which is used as a dummy variable. (The descriptive statistics of the socioeconomic variables are presented in the second section of Chapter 4.)

Other control variables in travel behavior studies are long-term and mid-term decisions. Residential selection and vehicle ownership can be considered long-term and mid-term decisions, respectively. Endogenous decisions such as residential self-selection have recently came under critical observation as an important potential contributor to travel behavior. Several studies have discussed that individuals' decisions for choosing a specific residential location or owning a car could influence their modes of travel (Boarnet & Crane, 2001; Bohte et al., 2007; Lerman, 1976; Schwanen & Mokhtarian, 2005; Srinivasan & Ferreira, 2002; J. Zhang & Van Acker, 2017). Using PCA, three factors were considered as an indicator of residential self-selection: Pro-Highway, Pro-Environment, and Pro-Family. The details of these factors are explained in the second section of Chapter 4.

In addition to socioeconomic factors and residential preferences, other studies have analyzed the effects of the built environment and urban form, commonly measured as the "D" factors: density, diversity, design, destination accessibility, distance to transit, development scale, and demographics (Cervero & Kockelman, 1997; Ewing & Cervero, 2010a). Density is one of the built environment factors that is frequently investigated in empirical studies (Bento, Cropper, Mobarak, & Vinha, 2005; Cervero & Murakami, 2010; Ewing & Cervero, 2010; Gomez-Ibanez et al., 2009).These studies presented an inverse relationship between VMT and density, concluding that residents in dense areas with compact development usually have lower VMT. For instance, by analyzing the travel distances of commuters in the Copenhagen Metropolitan Area, Næss (2006) found that residents who live in the suburbs with a low density of activities tend to travel longer distances with a higher rate of car use than residents located near the city center with higher density (p. 60).

Diversity is another built environment factor; it represents the mixture of land use. This measure is associated with the distribution of work and non-work activities in a given area (Ewing & Cervero, 2010). According to Ewing and Cervero (2010), there is a negative relationship between VMT and land use diversity. In a study by Kockelman (1997), mode choice and VMT are examined while considering control variables such as density, entropy index (land use balance), dissimilarity index of land use (mix index), and accessibility.

Understanding traffic congestion and its feedback on commuters' travel behaviors is another critical factor that has been mostly neglected in previous studies. Congestion and delays are often defined as the "impedance" for the movement of people and goods, which can be measured in terms of travel distance, travel time, and speed. Traffic congestion increases travel times and travel costs, which thereby influence different aspects of commuter travel behavior including VMT, VHT, PMT, and mode choice. In the present study, a delay score is used as a control variable for traffic congestion.

In the VMT model, built environment factors are represented by the following variables: access to free-parking at workplace, density-score, job/population balance score, transit score, and delay score. The process of calculating built environment factors and the corresponding descriptive statistics are discussed in Chapter 4.

Number of household vehicles is another factor that is affected by density. In the VMT model, number of household vehicles is considered an endogenous variable that is influenced by exogenous variables and directly affects VMT. The variables included in the SE model are defined in Table 23. In the VMT model, variables were grouped into three categories:

- *Outcome variable*: VMT per household.
- *Exogenous variables*: Explanatory factors comprising socioeconomic variables, self-selection variables, and built environment variables.
- *Endogenous variables*: Number of vehicles for each household, which can be influenced by other socioeconomic factors such as income and lifestyle. Table 23 presents the exogenous and endogenous variables used in VMT model.

Table 23. Variables Included in the VMT Model

Variables	Definition
Outcome Variable	
hh-vmt	Vehicle miles traveled per household
Exogenous Variables	
Socioeconomic Factors	
hh_size	Household size
hh_workers	Number of household workers
hh_child	Number of children in household
hh_income	Household income
home-rent	Living in rental homes (dummy variable)
Self-Selection Factors	
pro_hwy	Residential selection because of access to highway
pro-env	Residential selection because of access to public transit, walkability, or 30-minute travel time to workplace
pro-family	Residential selection because of school, changes in household, or close to friends and families
Built Environment Factors	
free-parking	Number of HH members with access to free parking at workplace
density-score	Combines population density, employment density, road density, and intersection density
Job/pop-score	Job/population balance
delay-score	Travel time delay
transit-score	Number of public transit routes
Endogenous Variable	
hh-vehicles	Number of household vehicles

VMT Model Specification

Analyzing traffic congestion and its interrelationship with land use requires consideration of exogenous and endogenous variables. The present research addresses this issue by using SEM—instead of single-equation models—to represent complex relationships between variables. SEM involves solving a set of equations, one for each "response" (i.e., endogenous variable) in the model. Variables that are solely predictors of other variables are termed "influences," or exogenous variables (Lei & Wu, 2007).

To estimate relationships in SEM, the Amos software package and maximum likelihood procedures were used to develop model specifications. Figure 25 presents the path diagram generated in SPSS AMOS for the best-fitting model. A path diagram is a visual representation of a system of simultaneous equation. In this diagram, the observed variables are enclosed in boxes. A straight, single-headed arrow represents a causal relationship between the variables connected by the arrow. A curved, two-headed arrow represents an association between two variables. The variables may be related for any of a number of reasons; the relationship may be due to both variables depending on some third factor(s), or the variables may have a causal relationship, but this remains unspecified (Bollen, 1989).

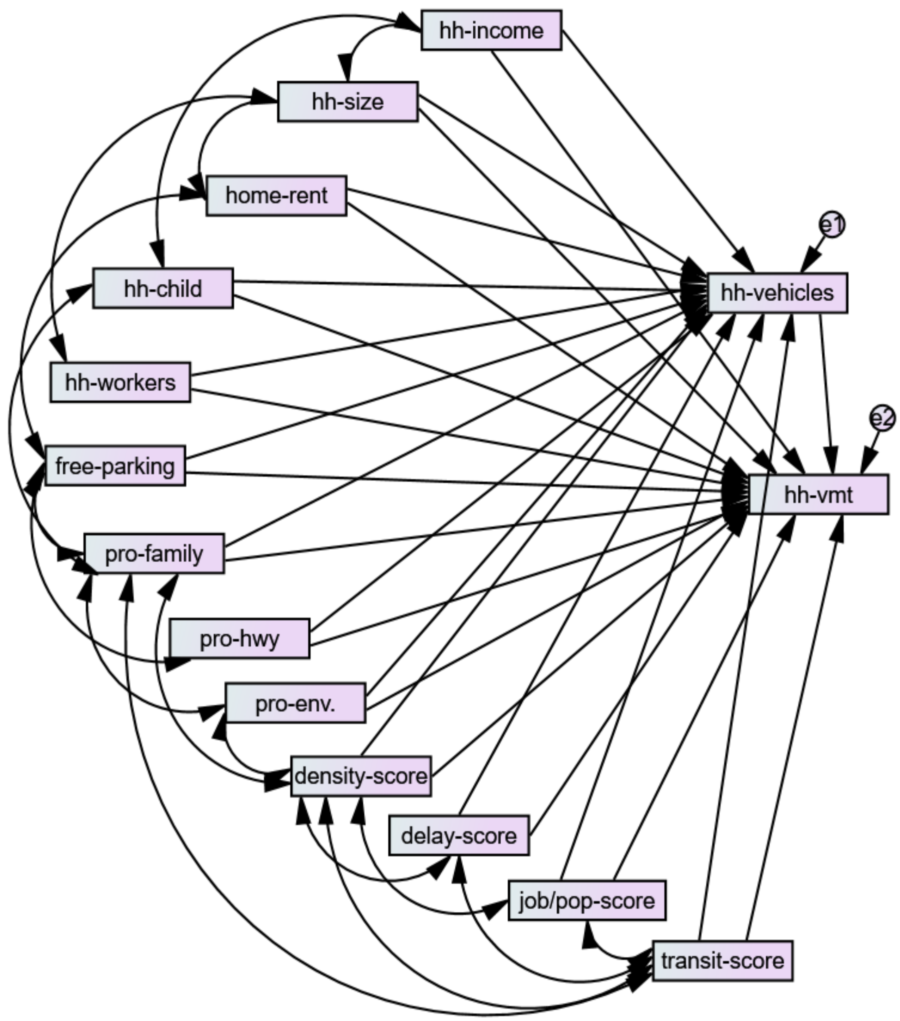

Figure 25. Causal Path Diagram Explaining VMT Per Household

SE Model Fit

Developing a well-defined measurement model is the purpose of statistical techniques that support creating a reliable model. There are different indices for evaluating an SE model's goodness-of-fit, as presented in Table 24. The most widely calculated measure is the X^2 value relative to the degrees of freedom. This is often referred to as the chi-square test. A significant chi-square result indicates an unsatisfactory model fit. According to Hox and Bechger (2007), hypothesized models can be rejected with a high chi-square value, which translates to a significant *p*-value. In other words, If the *p*-value associated with the value of X^2 is below .05, the hypothesized model should be rejected (Kaplan, 2000). In the present study's VMT SE model, the likelihood ratio chi-square results indicate a good model fit (X^2 = 22.29, df = 17, p = 0.173). Both the low ratio of chi-square to degrees of freedom and the *p*-value greater than .05 are indicators of the model's goodness of fit.

The likelihood ratio chi-square test is strongly sensitive to sample size. To overcome this limitation, researchers have focused on the development of alternative indices such as the Normed Fit Index (NFI), the Tucker- Lewis Index (TLI), the Comparative Fit Index (CFI), and the Parsimony-NFI (PNFI) (Kaplan, 2000). These indices provide relatively different perspectives on the fit of SE models. The details of these measures are beyond the scope of this research, though a comprehensive review of these indices can be found in Hu and Bentler (1995). According to Kaplan (2000), these indices are typically scaled to lie between 0 and 1, with 1 indicating perfect fit relative to the baseline model (p.107). The usual rule of thumb for these indices is that 0.95 is indicative of good fit relative to the baseline model. NFI and TLI, as well as other indices, utilize the likelihood ratio chi-square and assume that the model fits perfectly (p. 114).

Kaplan (2000) argues that these measures are too restrictive and that it is better to evaluate the approximate fit of the model. Root Mean Square Error of Approximation (RMSEA) is another measure that evaluates the approximate fit of a model. According to Kaplan (2000), on the basis of prior empirical examples, Steiger (1989) and Browne and Mels (1990) noted a "close fit" as a RMSEA value less than or equal to 0.05, while values between 0.08 and 0.1 are indicative of a mediocre fit. In the present study's VMT model, RMSEA is 0.013, which is within the 0.05 threshold.

These additional goodness-of-fit indices further indicate a good fit for the present study's VMT SE model. Table 24 presents the goodness-of-fit indices, with their corresponding cutoff values indicated in parentheses.

Table 24. SE Model Fit Results

Indicators	Value	Accepted Cutoff Values
Chi-square	22.29	-
Degrees of freedom	17	-
Probability level	0.174	> 0.05
Comparative Fit Index (CFI)	0.98	> 0.90
Normed Fit Index (NFI)	0.97	> 0.95
Non-Normed Fit Index (NNFI) (or the Tucker-Lewis Index: TLI)	0.98	> 0.90
Root Mean Square Error of Approximation (RMSEA)	0.013	< 0.05

Assessment of Multivariate Normality

According to Gao, Mokhtarian, and Johnston (2008), one of the main concerns in SEM is whether the sample data have a multivariate normal distribution. Using SPSS Amos, univariate and multivariate normalities are examined. As mentioned in the second section of Chapter 4, outliers were removed from the sample and the variables were transformed by taking the natural logarithm. This approach reduces the multivariate skewness and kurtosis of all variables collectively by reducing the univariate skewness and kurtosis of each individual variable. Table 25 presents the results of the analysis of the univariate normality for each variable and the multivariate normality of the selected sample (N = 1,729). As shown, when the critical ratio of multivariate kurtosis is smaller than 1.96, the absolute values of univariate kurtosis for all variables are equal to or smaller than 1 but are not necessarily 0. In this respect, according to Gao, Mokhtarian, and Johnston (2008), considering only multivariate kurtosis may be good enough for the purpose of assessing multivariate normality. As shown in Table 26, the critical ratio falls at the 1.96 cutoff value.

Table 25. Assessment of Normality in SEM

Variables	Skewness	C.R.	Kurtosis	C.R.
Socioeconomic Factor				
hh-vehicles	0.42	6.784	-0.881	-7.115
hh-size	-0.104	-1.686	-1.036	-8.369
hh-workers	0.851	13.745	-0.972	-7.849
hh-income	-0.47	-7.59	-0.122	-0.982
hh-child	0.779	12.581	0.092	0.74
Self-Selection Factor				
pro-environment	-0.8	-12.923	0.239	1.93
pro-highway	-1.237	-19.975	0.622	5.021
pro-family	-0.204	-3.293	-0.539	-4.356
Built Environment Factor				
delay-score	0.086	1.393	-1.048	-8.461
density-score	0.619	9.998	0.109	0.881
free-parking	0.976	15.765	0.002	0.015
job/pop-score	-1.207	-19.486	1.095	8.842
transit-score	0.388	6.263	-0.589	-4.754
Multivariate			1.426	1.249

VMT Model Results

Maximum likelihood was originally proposed as a method of estimation for econometric simultaneous equation models by Koopmans, Rubin, and Leipnik (1950). Substantially, Jöreskog (1969, 1970) explained the maximum likelihood technique for estimating a linear structural equation system and a general approach to confirmatory maximum likelihood factor analysis. The software program AMOS (Arbuckle, 2009) was used for this analysis. The main finding is that the level of traffic congestion—measured by delay score—is a significant predictor of VMT. Maximum likelihood estimates of the model parameters are provided in Table 26. This table includes unstandardized coefficients (*B*), standardized coefficients (Beta), standard error (SE), critical values (CR), and the resultant *p* values. The Unstandardized coefficient represents the amount by which the dependent variable changes if the explanatory variable is changed by 1 unit while keeping other variables constant. The standardized coefficient is measured in units of standard deviation. Standardizing coefficients indicate the relative importance of each coefficient in a regression model (Arbuckle, 2009). The following section provides the interpretations of percentage changes based on the unstandardized coefficients.

Table 26. Maximum Likelihood Estimates and Statistics for Direct Effects in SEM

Variables	Un-Std. Est. (B)	Std. Est. (Beta)	S.E.	C.R.	p
Socioeconomic Factor					
hh-vehicles <--- hh-size	0.358	0.352	0.026	13.78	***
hh-vehicles <--- hh-workers	0.135	0.102	0.03	4.515	***
hh-vehicles <--- hh-income	0.091	0.141	0.013	6.88	***
hh-vehicles <--- hh-child	-0.246	-0.11	0.047	-5.263	***
hh-vehicles <--- home-rent	-0.145	-0.135	0.021	-6.941	***
Self-Selection Factor					
hh-vehicles <--- pro-environment	-0.077	-0.126	0.013	-6.022	***
hh-vehicles <--- pro-highway	0.030	0.053	0.011	2.834	**
hh-vehicles <--- pro-family	0.063	0.029	0.043	1.461	0.144
Built Environment Factor					
hh-vehicles <--- delay-score	-0.085	-0.085	0.026	-3.311	***
hh-vehicles <--- density-score	-0.077	-0.128	0.017	-4.606	***
hh-vehicles <--- free-parking	0.047	0.066	0.014	3.336	***
hh-vehicles <--- job/pop-score	-0.084	-0.085	0.018	-4.718	***
hh-vehicles <--- transit-score	-0.034	-0.094	0.009	-3.604	***
Socioeconomic Factor					
hh-vmt <--- hh-vehicles	0.191	0.09	0.058	3.319	***
hh-vmt <--- hh-size	0.343	0.16	0.065	5.25	***
hh-vmt <--- hh-workers	-0.022	-0.008	0.072	-0.302	0.763
hh-vmt <--- hh-income	0.149	0.109	0.032	4.638	***
hh-vmt <--- hh-child	-0.026	-0.006	0.113	-0.234	0.815
hh-vmt <--- home-rent	0.036	0.016	0.051	0.719	0.472
Self-Selection Factor					
hh-vmt <--- pro-environment	-0.156	-0.121	0.031	-5.089	***
hh-vmt <--- pro-highway	0.148	0.124	0.025	5.809	***
hh-vmt <--- pro-family	0.037	0.008	0.103	0.362	0.718
Built Environment Factor					
hh-vmt <--- delay-score	-0.199	-0.094	0.062	-3.23	***
hh-vmt <--- density-score	-0.216	-0.17	0.04	-5.384	***
hh-vmt <--- free-parking	0.197	0.131	0.034	5.832	***
hh-vmt <--- job/pop-score	-0.174	-0.083	0.043	-4.055	***
hh-vmt <--- transit-score	-0.052	-0.068	0.023	-2.311	**

Note: Unstandardized Estimate (Un.Std. Est); Standardized Estimate (Std. Est); Standard Error (SE); Critical Value (CV).
*** p<0.001, ** p<0.01, * p<0.05

Vehicle Ownership

The results of the vehicle ownership model (see Table 27) indicate that all socioeconomic and residential preference factors, except for the pro-family factor, have a direct impact on vehicle ownership. Based on the standardized coefficients, household size is the most influential factor that increases the number of vehicles in a household (Beta = 0.358). Considering the unstandardized coefficient, a 1-unit increase in household size (i.e., 1 person) would lead to a 35.2 percent increase in the number of vehicles in a household.

As expected, number of workers has a positive impact on vehicle ownership while the number of children reduces the number of vehicles in a household. Adding one worker in a household would lead to a 13.5 percent increase in the number of vehicles in a household. In contrast, adding one child in a household would lead to a 24.6 percent decrease in the number of vehicles in a household.

The results suggest that the status of home ownership significantly affects the number of vehicles in a household. The coefficients of living at rental homes present a negative relationship between home ownership and car ownership. Considering the unstandardized coefficient estimates, living in a rental home is related to a 14.5 percent decrease in the number of vehicles in a household.

The model results also indicate that household income positively increases the number of vehicles in a household (B = 0.091). The coefficient of income indicates that a rise of 10 percent in income will produce a corresponding 0.9 percent increase in the number of vehicles in a household. The model outputs of residential preference indicate that households with pro-environmental attitudes tend to own fewer vehicles (B = -0.077). This observation is reinforced by the positive coefficient of the pro-highway factor (B = 0.03). Although the model coefficient shows the expected relationship between the pro-family factor and vehicle ownership, the result is not statistically significant at the .05 level.

The negative coefficients of density present a negative relationship between density and car ownership. For example, a 10 percent increase in density score is associated with a 0.7 percent decline in the number of vehicles in a household. As expected, households living in congested areas tend to own fewer vehicles than households living in uncongested areas. A rise of 10 percent in the delay score decreases the quantity of vehicles in a household by 0.8 percent. Likewise, there is a negative relationship between the job/population balance and the number of cars owned by a household (B = -0.084). The results also indicate that households located in areas with higher transit scores have fewer cars in their households (B = -0.034).

The effect of access to free parking on vehicle ownership presents an important finding for policy-making, especially in transportation planning. As shown in Table 26, households who have access to free parking are likely to own more vehicles than those that do not (B = 0.047). Ultimately, the model results indicate that household socioeconomic characteristics influence household vehicle ownership more than built environment factors.

VMT

Both socioeconomic and built environment factors influence daily VMT. As shown in Table 26, household size and income have a positive impact on VMT (B = 0.343 and 0.149, respectively). As presented in Table 26, the results were not statistically significant at the .05 level for socioeconomic factors addressing number of workers, number of children, and the status of home ownership.

The effect of vehicle availability in the household is positively associated with daily VMT per household (*B* = 0.191). This positive coefficient implies that by adding one automobile in a household, VMT will be increased by 19.1 percent. It should be noted that this variable is marginally over the cutoff at the 95% confidence level.

Residential preference is another significant factor that affects VMT. Households who selected their residential locations because of access to highways have higher VMTs (*B* = 0.148). In contrast, the pro-environment factor is another influential factor suppressing daily household VMT (*B* = -0.156).

Density factor is an important variable that mitigates household VMT (*B* = -0.216). The findings suggest that doubling the density score is associated with a VMT reduction of 21.6 percent. This elasticity is higher than the elasticity of -0.179 found in the study by Kim and Brownstone (2013) and it is lower than the elasticity of -0.24 found in the study by Ewing, Tian, and Lyons (2014). These elasticities showed negative impacts on VMT; however, the differences in elasticities are related to factors such as data aggregation and the methodology of calculating compactness or sprawl indices.

The sign on the coefficient of travel time delay is negative (*B* = -0.199). This implies that higher travel time delay is associated with lower VMT per household. In terms of percentage change, doubling travel time delay is associated with a 19.9 percent decrease in household VMT. Likewise, job/population balance shows a negative relationship with daily VMT in the household (*B* = -0.174). This value notes that a rise of 10 percent in job/population balance causes a corresponding 1.7 percent decrease in VMT per household; that is, households within areas with a higher density of activities and greater job/population balance have lower VMTs.

Access to public transit, measured by transit score, is another factor that decreases daily VMT per household. The results indicate that households located within areas with higher transit scores have moderately lower daily household VMT (*B* = -0.052). This value indicates that doubling the transit score results in a corresponding 5.2 percent decrease in VMT per household. In contrast, households with access to free parking at the workplace have a higher daily VMT (*B* = 0.197). This means that adding one person who has access to free parking increases the level of VMT per household by 19.7 percent. This provides evidence for transportation demand management to develop a public/private partnership with major employers to encourage the use of public transit and reduce access to free parking at the workplace.

Ultimately, these results suggest that daily VMT is more influenced by built environment variables and residential preferences, whereas a mid-term indicator such as vehicle ownership is highly associated with socioeconomic characteristics of households after controlling for self-selection and built environment factors. The results also indicate that vehicle ownership is another factor that increases household daily VMT while being dependent on various socioeconomic and built environment factors.

Total, Direct, and Indirect Effects

SEM distinguishes three types of effects: direct, indirect, and total effects. Direct effects refer to the influence of one variable on another unmediated by any other variables in the path model. The indirect effects of a variable are mediated by at least one intervening variable (Bollen, 1989). The sum of the direct and indirect effects is the total effect.

The direct and indirect effects of variables on one another and the total effects of different variables on VMT per household are summarized in Table 27. Based on the standardized estimates, household size and density factor have the strongest total effects on VMT (Beta = 0.192 and -0.182, respectively). Considering the direct effects, the density score has the highest direct impact on VMT (Beta = 0.17), followed by household size (Beta = 0.16) and access to free workplace parking (Beta = 0.131). Job/population balance and transit score have negative impacts on VMT, both directly (Beta = -0.083 and -0.068, respectively) and indirectly (Beta = -0.008). This implies that increasing job-population balance or transit score mitigate VMT per household. The pro-environment factor also has a significant total effect on VMT (Beta = -0.132). In contrast to the pro-environment factor, both direct and indirect effects of pro-highway groups were positive (Beta = 0.124 and 0.005, respectively), indicating that residential preference based on access to highways encourages households to drive more.

Table 27. Direct, Indirect, and Total Effects of Variables on VMT per Household - Standardized Estimates

Variables	Direct Effect	Indirect Effect	Total Effect
Socioeconomic Factors			
hh-vehicles	0.090	0.00	0.090
hh-Size	0.160	0.032	0.192
hh-num-workers	-0.008	0.009	0.001
hh-income	0.109	0.013	0.122
hh-num-children	-0.006	-0.010	-0.016
Self-selection Factor			
pro-environment	-0.121	-0.011	-0.132
pro-highway	0.124	0.005	0.129
pro-family	0.008	0.003	0.011
Built Environment Factors			
free-parking	0.131	0.006	0.137
home-rent	0.016	-0.012	0.004
delay-score	-0.094	-0.008	-0.102
density-score	-0.170	-0.012	-0.182
job/pop-score	-0.083	-0.008	-0.091
transit-score	-0.068	-0.008	-0.076

Mode Choice Model Using GSEM

The mode choice model is based on trip level-data and examines the probability of choosing modes of travel. Analyzing disaggregated data provides an opportunity to examine not only the travel behavior of households or individuals but also to analyze travel behavior at the trip level. The trip-level model was developed by using GSEM with a logit-link function to handle discrete dependent variables. As mentioned in the previous chapter, GSEM is the combination of SEM capabilities with a GLM estimation framework to build models with response variables that are not continuous measures. Whereas in SEM responses are continuous and models are linear regressions, in GSEM responses are continuous or binary, ordinal, count, or multinomial. In other words, GSEM techniques are an extension of SEM with the purpose of developing multilevel models with discrete outcomes (StataCorp, 2017). In this research, recursive GSEM with causality paths directed at mode choices was developed to examine the association between mode choice and other factors such as demographics, the built environment, and level of traffic congestion. The following section explains the variables used in the mode choice model, discusses the model fit, and explores the model results.

Mode Choice Model Variables

The mode choice model comprises discrete outcome variables and multiple explanatory factors. The outcome variables in this model include four modes of travel addressing driving alone, carpooling (rideshare), transit (bus or train), and non-motorized (walk or bike) modes. In this analysis, driving alone is considered the reference variable in the logit models, and the probability of other modes is compared to this reference variable. Table 28 presents the four mode choice outcomes that were tested in the mode choice model. Using GSEM with a logit function, the probability of each mode of travel is estimated as follows:

- Probability of driving alone relative to other modes
- Probability of carpooling relative to driving alone
- Probability of using public transit (bus or train) relative to driving alone.
- Probability of using a non-motorized mode (walk or bike) relative to driving alone

Table 28. Mode Choice Alternatives

Mode Splits	Definition	Source
Drive Alone	Commuters drove	PSRC 2015
Carpooling	Shared trip with others	PSRC 2015
Transit (bus\train)	Commuters took public transit	PSRC 2015
Non-Motorized (walking\biking)	Walking\biking to the destination	PSRC 2015

To determine the factors that influence the choice of travel mode, a recursive model with a logit link function was specified. This model includes explanatory variables such as residential self-selection, built environment factors, and socioeconomic characteristics of commuters. The explanatory factors were selected based on relevant theories, previous experimental studies, and model fits. Table 29 displays a list of explanatory variables and their original sources. These factors were used in the model specifications.

As discussed in the previous section, the utility function includes an essential set of explanatory variables. These variables are based on theory and prior studies, as well as time-related mobility measures which are important for individuals' travel choice behaviors. To examine the effects of socioeconomic factors, several utility equation structures were tested using the demographic variables from the travel survey data.

Factors such as gender, age, and individual preferences for selecting home locations were examined in this study.

Table 29. Variables Included in the Mode Choice Models

Variable	Definition	Source
Trip-Maker Attribute		
age	Age of commuter	PSRC 2015
male (Y N)	If the individual is male	PSRC 2015
hh_income	Natural log of household income	PSRC 2015
hh_vehicles	Number of vehicles in household	PSRC 2015
hh_size	Household size	PSRC 2015
Full time (Y N)	Full-time employed	PSRC 2015
Education	Level of education	PSRC 2015
Residential-Location Preferences		
How important when choosing current home:		
res_factors_transit	Being close to public transit	PSRC 2015
res_factors_hwy	Being close to highway	PSRC 2015
res_factors_walk	Having a walkable neighborhood and being near local activities	PSRC 2015
Trip Purpose		
tp_hbw (Y N)	Home-based-work trip	PSRC 2015
tp_shop (Y N)	Shopping trip	PSRC 2015
tp_nhb (Y N)	Non-home-based trip	PSRC 2015
tp_socrec (Y N)	Social or recreational trip	PSRC 2015
Built Environment Attributes		
delay_od	Natural log of the amount of travel time delay (minutes)	Google Maps API
density_origin.	Natural log of activity density at origin (total housing units + employment per acre)	LEHD, Census
density_destin.	Natural log of activity density at destination (total housing units + employment per acre)	LEHD, Census
jobpop_origin.	Natural log of job/population balance at origin	LEHD, Census
jobpop_destin.	Natural log of job/population balance at destination	LEHD, Census
distance_od	Natural log of distance to destination	Google Maps
walkscore_origin.	Natural log of walk score at origin	Walk Score
walkscore_destin.	Natural log of walk score at destination	Walk Score
transitscore_origin.	Natural log of transit score at origin	Transit Score
transitscore_destin.	Natural log of transit score at destination	Transit Score

In the mode choice model, the effects of the following socioeconomic factors are tested in the model specifications: age; gender; income; number of vehicles in households; Household size; Employment status, and Level of education. Details of socioeconomic variables and descriptive statistics of these variables are reported in the second section of Chapter 4. In addition to socioeconomic factors, the effects of trip-purpose on selecting each model of travel is considered in the GSEM model addressing these trip purposes: home-based work (HBW), non-home-based (NHB), shopping trips (SHOP), and social and recreational trips (SOCREC).

The characteristics of the built environment are also important factors that influence travel behavior. As shown in Table 29, built environment factors are considered at the origin and destination of trips and address activity density, job/population balance, walk score, and transit score. Additionally, travel time delay and trips distance for each trip were tested in the mode choice model.

Using GSEM with a logit function, the variables described above were examined in the mode choice model to test potential interactions with the travel time coefficients and to determine whether respondents' trips or personal characteristics significantly influenced their choices. After reviewing the significance of each variable, the final model specification was chosen based on model fit, the intuitiveness and reasonableness of the model coefficients, and the expected application of the model results.

Mode Choice Model Specification

The mode choice model comprises five sub-models that separately investigated the influence of socioeconomic factors, residential preference, and built environment variables on the probability of carpooling, non-motorized trips, and transit usage. The first model, the base model, includes only socio-demographic characteristics of commuters.

The second model includes the first model plus the influence of residential preferences on selecting specific modes of travel. In the third model, the effects of trip purpose are added to the second model. The trip purpose factors are represented by HBW, SHOP, NHB, and SOCREC trips. The forth model includes the third model plus built environment factors that are represented by activity density, transit score, walk score, and job/population balance at the near-origin and near-destination of trips. In the fifth model (i.e., the full model; see Figure 26), travel time delay is added to test the effects of congestion on travel mode choice and how travel time delay influences model fit.

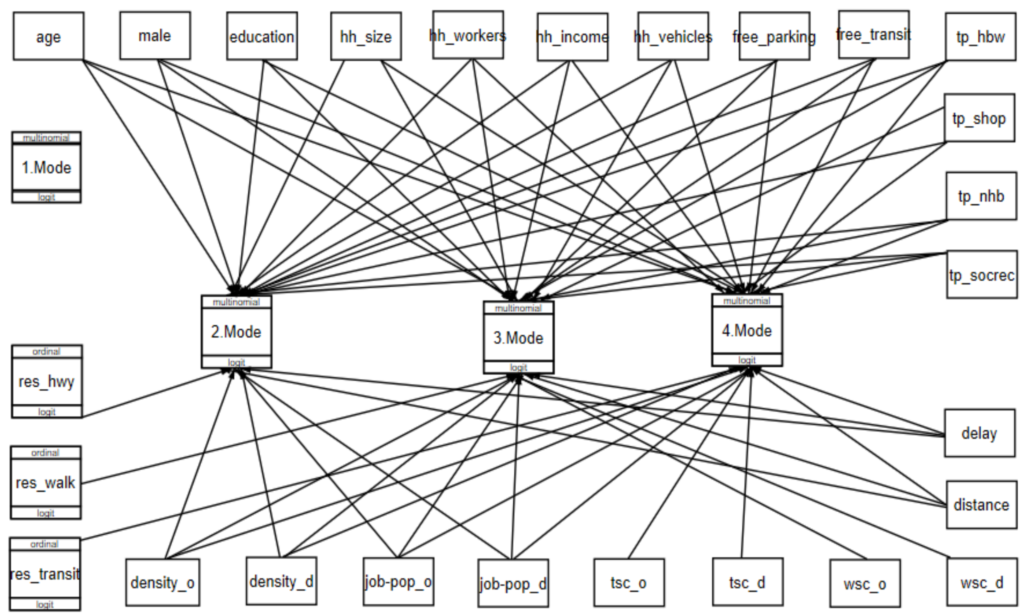

Figure 26. GSEM Diagram Explaining Commuter's Mode Choice

GSEM Model Fit

Most of the statistics such as CFI, NFI, and RMSEA that are reported for SEM are not available after developing GSEM because of the type of estimation that it uses (Baum, 2016). These statistics are a function of the model chi-square test. The model chi-square test involves an estimate of the variances and covariances of observed exogenous variables. GSEM in STATA 15 does not estimate these parameters for the observed exogenous variables when fitting models with GSEM. Therefore, GSEM cannot estimate the model chi-square test and other statistics that are functions of this test. However, the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) can be calculated to compare different models. Therefore, AIC and BIC were used to examine model fit.

The mathematical underpinning of AIC and BIC are beyond the scope of and focus of this research. However, the broad outlines of AIC and BIC can be explained as follows: To begin, AIC and BIC try to balance good fit with parsimony using penalized likelihood criteria, where BIC penalizes complexity more heavily depending on sample size. In contrast, AIC's penalty for complexity does not depend on sample size. The use of the AIC and BIC requires fitting several competing models (Kaplan, 2000, p. 117). The model with the lowest AIC or BIC value among the competing models is deemed to fit the data best from a predictive point of view. Table 30 indicates the results of model fit examined via AIC and BIC.

Table 30. Model Fit Indices

Model Specifications	Model 1	Model 2	Model 3	Model 4	Model 5
	Base	Res. Preference	Trip Purpose	Built Env.	Travel Time Delay
Model Fit Indices					
Log-Likelihood [df]	-15,792.8 [30]	-15,586.0 [33]	-14,483.6 [45]	-7,759.2 [64]	-7,624.6 [67]
AIC	31,645.64	31,238.08	29,057.37	15,646.48	15,383.34
BIC	31,873.35	31,488.55	29,398.92	16,132.25	15,891.87

In analyzing the effects of travel time delay on mode choice, Model 5—which specifies travel time delay—reports both the lowest AIC and BIC values. The first and simplest model does not perform well despite being limited to socioeconomic variables (BIC ranks 5th, AIC ranks 5th). Model 4 shows that adding built environment factors, including density, walk score, and transit score have an important role in reducing AIC and BIC values. This suggests that extending the model by including the built environment factors provides a more reliable model. The following section describes the results of the full model and interprets the coefficient estimates and corresponding odds ratios.

GSEM Mode Choice Model Results

The estimated logit coefficients of the full model are presented in Table 31 through Table 33. These coefficients can be used to predict carpooling, transit, and non-motorized mode choices relative to drive-alone travel. The majority of estimated parameters were statistically significant at the 95% confidence level.

Table 31. Coefficients of Multinomial Logit Model for Predicting Carpooling Mode Choice Relative to Drive-Alone Travel

Variables	Coef.	Std. Err.	*z*	*P*>|*z*|	[95% Conf. Interval]	
Mode 1: Drive Alone	*(base outcome)*					
Mode 2: Carpooling						
age	-0.01	0.02	-0.61	0.54	-0.06	0.03
male	0.02	0.06	0.34	0.73	-0.10	0.14
education	-0.14	0.02	-8.00	0.00	-0.18	-0.11
hh_size	0.81	0.03	23.65	0.00	0.74	0.88
hh_workers	-0.62	0.05	-13.54	0.00	-0.70	-0.53
hh_income	-0.05	0.05	-1.07	0.28	-0.14	0.04
hh_vehicles	0.32	0.04	8.75	0.00	0.25	0.39
access_free_transit	-0.03	0.11	-0.29	0.77	-0.25	0.18
access_free_parking	-0.15	0.07	-1.99	0.05	-0.29	0.00
res_factors_hwy	-0.03	0.02	-1.39	0.16	-0.07	0.01
tp_hbw	-2.39	0.12	-19.81	0.00	-2.62	-2.15
tp_shop	-0.07	0.08	-0.93	0.35	-0.22	0.08
tp_nhb	-0.54	0.07	-8.04	0.00	-0.67	-0.41
tp_socrec	0.74	0.07	10.32	0.00	0.60	0.89
density_origin	0.60	0.02	24.38	0.00	0.55	0.65
density_destin	0.77	0.03	29.59	0.00	0.72	0.82
jobpop_origin	0.27	0.04	6.64	0.00	0.19	0.35
jobpop_destin	0.67	0.05	13.58	0.00	0.57	0.77
distance_od	-0.13	0.05	-2.87	0.00	-0.23	-0.04
delay_od	0.65	0.05	12.49	0.00	0.54	0.75
_cons	-3.18	0.52	-6.06	0.00	-4.21	-2.15

Note: Coefficient (Coef.); Standardized Error (Std. Err.)

Table 32. Coefficients of Multinomial Logit Model for Predicting Transit Mode Choice Relative to Drive-Alone Travel

Variables	Coef.	Std. Err.	*z*	*P*>|*z*|	[95% Conf. Interval]	
Mode 1: Drive Alone	*(base outcome)*					
Mode 3: Transit (bus\train)						
age	0.03	0.04	0.98	0.33	-0.04	0.11
male	0.11	0.10	1.06	0.29	-0.09	0.31
education	-0.31	0.03	-9.68	0.00	-0.38	-0.25
hh_size	0.58	0.06	9.38	0.00	0.46	0.70
hh_workers	-0.41	0.09	-4.78	0.00	-0.58	-0.24
hh_income	-0.39	0.08	-5.08	0.00	-0.55	-0.24
hh_vehicles	-0.59	0.08	-7.46	0.00	-0.74	-0.43
access_free_transit	1.24	0.14	9.05	0.00	0.97	1.51
access_free_parking	-1.60	0.17	-9.67	0.00	-1.93	-1.28
res_factors_transit	0.24	0.04	5.62	0.00	0.16	0.33
tp_hbw	-0.68	0.16	-4.34	0.00	-0.98	-0.37
tp_shop	-0.33	0.15	-2.24	0.03	-0.62	-0.04
tp_nhb	-0.79	0.13	-6.15	0.00	-1.04	-0.54
tp_socrec	0.26	0.14	1.94	0.06	0.00	0.53
density_origin	0.88	0.04	19.84	0.00	0.80	0.97
density_destin	0.86	0.04	19.50	0.00	0.77	0.95
jobpop_origin	0.37	0.08	4.49	0.00	0.21	0.54
jobpop_destin	0.26	0.08	3.12	0.00	0.10	0.42
transitscore_origin	1.23	0.18	6.68	0.00	0.87	1.60
transitscore_destin	1.11	0.17	6.50	0.00	0.77	1.44
distance_od	0.74	0.11	7.01	0.00	0.54	0.95
delay_od	0.53	0.12	4.36	0.00	0.29	0.76
_cons	-12.47	1.16	-10.73	0.00	-14.75	-10.19

Note: Coefficient (Coef.); Standardized Error (Std. Err.)

Table 33. Coefficients of Multinomial Logit Model for Predicting Non-Motorized Mode Choice Relative to Drive-Alone Travel

Variables	Coef.	Std. Err.	*z*	*P*>|*z*|	[95% Conf. Interval]	
Mode 1: Drive Alone	*(base outcome)*					
Mode 4: Non-Motorized (walking\biking)						
age	-0.05	0.03	-1.81	0.07	-0.11	0.00
male	-0.40	0.08	-4.87	0.00	-0.57	-0.24
education	-0.03	0.03	-1.28	0.20	-0.08	0.02
hh_size	0.41	0.05	8.44	0.00	0.31	0.50
hh_workers	-0.29	0.06	-4.55	0.00	-0.42	-0.17
hh_income	-0.06	0.06	-0.90	0.37	-0.18	0.07
hh_vehicles	0.08	0.06	1.44	0.15	-0.03	0.19
access_free_transit	0.62	0.13	4.85	0.00	0.37	0.87
access_free_parking	-0.53	0.11	-5.02	0.00	-0.74	-0.32
res_factors_walk	0.12	0.04	3.38	0.00	0.05	0.19
tp_hbw	-0.15	0.15	-1.02	0.31	-0.45	0.14
tp_shop	-0.78	0.12	-6.76	0.00	-1.01	-0.56
tp_nhb	-1.25	0.10	-12.83	0.00	-1.44	-1.06
tp_socrec	1.53	0.10	15.22	0.00	1.34	1.73
density_origin	0.74	0.04	18.93	0.00	0.67	0.82
density_destin	0.72	0.04	18.13	0.00	0.64	0.80
jobpop_origin	0.24	0.08	3.10	0.00	0.09	0.40
jobpop_destin	1.04	0.09	11.82	0.00	0.87	1.22
walkscore_origin	0.37	0.10	3.59	0.00	0.17	0.57
walkscore_destin	0.53	0.11	4.97	0.00	0.32	0.74
distance_od	-1.92	0.06	-30.01	0.00	-2.05	-1.80
delay_od	0.79	0.07	11.22	0.00	0.65	0.93
_cons	-7.38	0.79	-9.39	0.00	-8.92	-5.84

Note: Coefficient (Coef.); Standardized Error (Std. Err.)

Table 34 through Table 36 present the odds ratio of the variables in the full model addressing carpooling, transit, and non-motorized modes relative to driving alone (as the reference variable). An odds ratio indicates the effects of a variable on the probability of an event; it is a ratio of the probability of one event to the probability of another event (Crown, 1998). The odds ratio can be obtained by exponentiating the coefficient of each variable. For the odds ratio, a coefficient of 1 leaves the odds unchanged, a coefficient greater than 1 increase the odds, and a coefficient less than 1 decreases the odds (Pampel, 2000). It is necessary to note that a 1-unit increase in a log transformed variable translates to a 172 percent increase in a non-transformed variable. So, the interpretation of transformed variables is adjusted based on this relationship.

Table 34. Probability of Carpooling Mode Choice Relative to Drive-Alone Travel

Variables	exp(b)	Std. Err.	*z*	*P*>|*z*|	[95% Conf. Interval]	
Mode 1: Drive Alone	*(base outcome)*					
Mode 2: Carpooling						
age	0.99	0.02	-0.61	0.54	0.95	1.03
male	1.02	0.06	0.34	0.73	0.91	1.15
education	0.87	0.02	-8.00	0.00	0.84	0.90
hh_size	2.25	0.08	23.65	0.00	2.10	2.40
hh_workers	0.54	0.02	-13.54	0.00	0.49	0.59
hh_income	0.95	0.04	-1.07	0.28	0.87	1.04
hh_vehicles	1.38	0.05	8.75	0.00	1.28	1.48
access_free_transit	0.97	0.11	-0.29	0.77	0.78	1.20
access_free_parking	0.86	0.06	-1.99	0.05	0.75	1.00
res_factors_hwy	0.97	0.02	-1.39	0.16	0.93	1.01
tp_hbw	0.09	0.01	-19.81	0.00	0.07	0.12
tp_shop	0.93	0.07	-0.93	0.35	0.80	1.08
tp_nhb	0.58	0.04	-8.04	0.00	0.51	0.66
tp_socrec	2.11	0.15	10.32	0.00	1.83	2.43
density_origin	1.82	0.04	24.38	0.00	1.73	1.91
density_destin	2.16	0.06	29.59	0.00	2.05	2.27
jobpop_origin	1.32	0.05	6.64	0.00	1.21	1.43
jobpop_destin	1.96	0.10	13.58	0.00	1.77	2.15
distance_od	0.87	0.04	-2.87	0.00	0.80	0.96
delay_od	1.91	0.10	12.49	0.00	1.72	2.11
_cons	0.04	0.02	-6.06	0.00	0.01	0.12

Table 35. Probability of Using Transit Mode Choice Relative to Drive-Alone Travel

Variables	exp(b)	Std. Err.	z	*P*>|*z*|	[95% Conf. Interval]	
Mode 1: Drive Alone	(base outcome)					
Mode 3: Transit (bus\train)						
age	1.04	0.04	0.98	0.33	0.97	1.11
male	1.12	0.11	1.06	0.29	0.91	1.36
education	0.73	0.02	-9.68	0.00	0.68	0.78
hh_size	1.79	0.11	9.38	0.00	1.58	2.02
hh_workers	0.66	0.06	-4.78	0.00	0.56	0.79
hh_income	0.67	0.05	-5.08	0.00	0.58	0.78
hh_vehicles	0.55	0.04	-7.46	0.00	0.47	0.65
access_free_transit	3.47	0.48	9.05	0.00	2.65	4.54
access_free_parking	0.20	0.03	-9.67	0.00	0.15	0.28
res_factors_transit	1.28	0.06	5.62	0.00	1.17	1.39
tp_hbw	0.51	0.08	-4.34	0.00	0.37	0.69
tp_shop	0.72	0.11	-2.24	0.03	0.54	0.96
tp_nhb	0.45	0.06	-6.15	0.00	0.35	0.58
tp_socrec	1.30	0.18	1.94	0.05	1.00	1.70
density_origin	2.42	0.11	19.84	0.00	2.22	2.64
density_destin	2.36	0.10	19.50	0.00	2.17	2.58
jobpop_origin	1.45	0.12	4.49	0.00	1.23	1.71
jobpop_destin	1.29	0.11	3.12	0.00	1.10	1.52
transitscore_origin	3.44	0.63	6.68	0.00	2.39	4.93
transitscore_destin	3.03	0.52	6.50	0.00	2.17	4.23
distance_od	2.10	0.22	7.01	0.00	1.71	2.59
delay_od	1.69	0.20	4.36	0.00	1.34	2.14
_cons	0.00	0.00	-10.73	0.00	0.00	0.00

Table 36. Probability of Selecting Non-Motorized Mode Choice Relative to Drive-Alone Travel

Variables	exp(b)	Std. Err.	z	*P*>|*z*|	[95% Conf. Interval]	
Mode 1: Drive Alone	*(base outcome)*					
Mode 4: Non-Motorized (walking\biking)						
age	0.95	0.03	-1.81	0.07	0.89	1.00
male	0.668	0.06	-4.87	0.00	0.57	0.79
education	0.97	0.02	-1.28	0.20	0.92	1.02
hh_size	1.50	0.07	8.44	0.00	1.37	1.65
hh_workers	0.75	0.05	-4.55	0.00	0.66	0.85
hh_income	0.95	0.06	-0.90	0.37	0.84	1.07
hh_vehicles	1.08	0.06	1.44	0.15	0.97	1.21
access_free_transit	1.86	0.24	4.85	0.00	1.45	2.39
access_free_parking	0.59	0.06	-5.02	0.00	0.48	0.72
res_factors_walk	1.13	0.04	3.38	0.00	1.05	1.21
tp_hbw	0.86	0.13	-1.02	0.31	0.64	1.15
tp_shop	0.46	0.05	-6.76	0.00	0.36	0.57
tp_nhb	0.29	0.03	-12.83	0.00	0.24	0.35
tp_socrec	4.64	0.47	15.22	0.00	3.81	5.65
density_origin	2.10	0.08	18.93	0.00	1.95	2.27
density_destin	2.05	0.08	18.13	0.00	1.90	2.22
jobpop_origin	1.28	0.10	3.10	0.00	1.09	1.49
jobpop_destin	2.84	0.25	11.82	0.00	2.39	3.38
walkscore_origin	1.45	0.15	3.59	0.00	1.18	1.77
walkscore_destin	1.70	0.18	4.97	0.00	1.38	2.09
distance_od	0.15	0.01	-30.01	0.00	0.13	0.17
delay_od	2.20	0.16	11.22	0.00	1.92	2.53
_cons	0.00	0.00	-9.39	0.00	0.00	0.00

Effects of Socioeconomic Variables on Mode Choice

Among the socioeconomic factors, vehicle availability, household size, number of workers, and subsidies for free transit or free parking are the influential predictors of carpooling, transit usage, and non-motorized mode.

Age exceeds the significance level of .05 when comparing carpooling relative to drive-alone mode. Addressing transit and non-motorized modes, the coefficients of age are negative, indicating that older commuters are more likely to drive alone relative to walking\biking or taking transit.

The coefficient for the male dummy variable was found to be negative and statistically significant for the non-motorized mode (B = -0.40). The odds ratio suggests that males are 1.49 times more likely to drive alone than walking\biking. In terms of percent change, the odds of men driving alone are 49 percent higher than for women relative to non-motorized modes. The coefficients of gender were not statistically significant for carpooling and transit usage.

The results indicate that level of education is negatively associated with carpooling (B = -0.14) and taking public transit (B = -0.31). For people with a higher level of education, the probability of carpooling and taking transit are 0.87 and 0.73 times lower than driving alone, respectively.

At the 95% confidence level, household size is positively associated with carpooling (B = 0.81), transit usage (B = 0.58), and non-motorized modes (B = 0.41). These positive coefficients indicate that a larger household size is associated with a higher likelihood of carpooling, using transit, and choosing non-motorized modes relative to driving alone. For example, a one-person increase in household size would lead to a 125 percent increase in choosing carpooling relative to driving alone. The odds of taking transit is 1.79 times greater than the odds of driving alone mode for a one-person difference in household size. Considering non-motorized mode choice, the odds ratio indicates that commuters with a one-person increase in their household size are 1.5 times more likely to choose a non-motorized mode of travel.

At the 95% confidence level, the number of workers is negatively associated with carpooling (B = -0.62), taking public transit (B = -0.41), and choosing a non-motorized mode (B = -0.29). These findings suggest that commuters with a higher number of workers in the household are more likely to drive alone relative to all other modes. For example, a one-worker increase in a household would lead to an 85 percent increase in driving alone compared to carpooling. The odds of driving alone are 1.50 times greater than the odds of taking transit with one additional worker in a household. The odds ratio indicates that commuters with one additional worker in the household are 1.34 times more likely to choose driving alone over a non-motorized mode of travel.

The coefficient of income is negative (B = -0.39) and statistically significant in explaining transit usage at the 95% confidence level. The odds ratio indicates that the probability of driving alone is 1.48 times greater than taking transit for a 1-unit increase in log of income. Income was not statistically significant in explaining carpooling and non-motorized modes.

Effects of Vehicle Ownership on Mode Choice

The findings present an unexpected result with a positive relationship between the number of vehicles and the probability of carpooling (B = 0.32). This positive coefficient indicates that commuters with more vehicles in their household have a higher probability of carpooling relative to driving alone. The reason might be related to other factors such as income, household size, and the number of adults with an active driver's license in the household. As a result, some families might own several cars but share rides because of age limitations, physical ability, or having household members without driver's licenses.

As expected, vehicle availability is negatively associated with taking transit (*B* = -0.59). Based on the logit coefficient, a higher number of vehicles is associated with a lower likelihood of taking public transit relative to driving alone (OR = 0.55). This odds ratio indicates that an increase of one automobile would lead to an 80.3 percent increase in the probability of driving alone relative to taking transit (OR = 1/0.55). This implies that taking public transit is the least preferred option when more automobiles are available.

The effects of number of vehicles in the household on non-motorized modes is not statistically significant at the 95% confidence interval in the full model. In fact, the effect of vehicle ownership lost its significance after including built environment variables. In the basic models, the negative coefficients indicate that commuters with more vehicles in their household have a lower probability of choosing non-motorized modes relative to driving alone.

Effects of Residential Preferences on Mode Choice

Among residential preference variables, access to a highway exceeds the significance level of .05. Considering transit and walkability, the result of residential preference is aligned with expectations. The results show that there is a positive relationship between choosing a non-motorized mode and selecting residential location based on walkability (*B* = 0.12). The odds ratio indicates that those groups are 1.13 times more likely to choose walking\biking than driving alone (OR = 1.13). Similarly, those who selected their residential location because of access to transit have a higher probability of choosing transit modes (*B* = 0.24). The odds ratio indicates that the likelihood of taking transit is 1.28 times greater than driving alone for those who selected their residential location because of access to transit (OR = 1.28).

Effects of Transportation Subsidy on Mode Choice

As mentioned previously, having a free transit pass and access to free parking at the workplace were investigated in the mode choice model. Considering transit subsidy, the results show that having a free transit pass is positively and strongly associated with taking transit (*B* = 1.24). The odds ratio suggests that the likelihood of taking transit is 3.5 times greater than driving alone for those who have access to a free transit pass (OR = 3.47). The results also indicate that access to free transit not only increases the probability of taking transit but also increases the likelihood of choosing a non-motorized mode relative over driving alone (*B* = 0.62). The odds ratio indicates that the likelihood of choosing a non-motorized mode is 1.86 times greater than driving alone for those who have free transit pass (OR = 1.86).

In contrast, commuters with access to free parking at their workplace have a higher probability of choosing to drive alone over all other modes. The results show that access to free parking at the workplace is negatively associated with carpooling (*B* = -0.15), taking public transit (*B* = -1.60), or choosing a non-motorized mode (*B* = -0.53) relative to driving alone. Based on the odds ratio, the probability of driving alone is 1.16 times greater than carpooling for commuters who have access to free parking at the workplace (OR = 1/ 0.86). Also, the probability of driving alone is 1.69 times greater than walking\biking for commuters who have access to free parking at the workplace (OR = 1/ 0.59). Similarly, the probability of driving alone is 5 times greater than taking transit for commuters who have access to free parking at the workplace (OR = 1/ 0.2). This higher odds ratio implies the importance of policies that support parking pricing, transit subsidies, and encourage employers and workers to use public transit or charge fees for facilities such as access to parking at the workplace. Note that causality could be the other way—commuters who prefer public transit might prefer employers with transit benefits or request a transit subsidy from their employer. Analyzing this causality requires further investigation beyond the scope of this research.

Effects of Trip Purpose on Mode Choice

The signs of the home-based-work trip coefficients are negative for taking transit (*B* = -0.68), and carpooling (*B* = -2.39). This implies that the likelihood of carpooling or taking transit decreases relative to driving alone when commuters conduct home-based-work trips. The likelihood of driving alone is 10.8 (OR = 1/ 0.09) times greater than carpooling for those who conducted home-based-work trips. This high odds ratio indicates that carpooling is the least preferred choice for commuters when conducting home-based-work trips. Also, the probability of driving alone is 1.97 (OR = 1/ 0.51) times greater than taking transit for commuters who conducted home-based-work trips. The effects of home-based-work trips on non-motorized trips was not statistically significant at the .05 level.

At the 95% confidence level, the sign of the non-home-based trip coefficients are negative for carpooling (*B* = -0.54), taking transit (*B* = -0.79), and non-motorized modes (*B* = -1.25). This implies that the likelihood of driving alone increases relative to all other modes for commuters who conducted non-home-based trips. The odds ratio of conducting non-home-based trips suggests that the probability of driving alone is 1.72, 2.2, and 3.49 times greater, respectively, than carpooling, taking transit, and walking/biking.

Similarly, conducting shopping trips decreases the likelihood of taking transit (*B* = -0.33) and walking\biking (*B* = -0.78) relative to driving alone. For commuters who conducted shopping trips, the odds ratios suggest that the probability of driving alone is 1.39 and 2.19 times greater, respectively, than taking transit and walking/biking. The effect of shopping trips was not statistically significant on carpooling.

At the 95% confidence level, the signs of the social and recreational trip coefficients are positive for carpooling (*B* = 0.74) and walking\biking (*B* = 1.53). The odds ratio indicates that commuters who conducted social and recreational trips are 2.11 times more likely to choose carpooling relative to driving alone. The probability of walking\biking is 4.64 times greater than driving alone for those who conducted social and recreational trips. The effects of social and recreational trips on taking transit were marginally past the cutoff at the 95% confidence level.

Effects of Built Environment on Mode Choice

Regarding built environment factors, activity density (i.e., the total of population and employment per acre) at the near-origin of trips is positively associated with carpooling (*B* = 0.60), transit mode (*B* = 0.88), and non-motorized modes (*B* = 0.74). Considering activity density at the near-origin of trips, the odds ratios indicate that the probability of carpooling, taking transit, and walking/biking is 1.82, 2.42, and 2.10 times greater, respectively, than driving alone for a 1-unit increases in the log of activity density at the near-origin of trips. That means by doubling the activity density at the near-origin of trips, the probability of carpooling, taking transit, and walking/biking is 1.51, 1.84, and 1.67 times greater, respectively, than driving alone.

Similarly, activity density at the near-destination of trips is positively associated with carpooling (*B* = 0.77), transit mode (*B* = 0.86), and non-motorized modes (*B* = 0.72).

Addressing activity density at near-destinations, the odds ratios indicate that the probability of carpooling, taking transit, and walking/biking are 2.16, 2.36, and 2.05 times greater, respectively, than driving alone for a 1-unit increases in the log activity density at the near-destination of trips. That means by doubling the activity density at the near-destinations of trips, the probability of carpooling, taking transit, and walking/biking is 1.70, 1.81, and 1.64 times greater, respectively, than driving alone.

The model also indicates that a higher job/population balance at the near-origin or near-destination of trips decreases the probability of driving alone relative to all other modes. At the 95% confidence level, job-population balance at the near-origin of trips is positively associated with carpooling (B = 0.27), transit mode (B = 0.37), and non-motorized modes (B = 0.24). The odds ratios indicate that the probability of carpooling, taking transit, and walking/biking are 1.32, 1.45, and 1.28 times greater, respectively, than driving alone for a 1-unit increase in the log of job/population balance at the near-origin of trips. That means by doubling the job/population balance at the near-origin of trips, the probability of carpooling, taking transit, and walking/biking is 1.21, 1.29, and 1.18 times greater, respectively, than driving alone.

Likewise, job/population balance at the near-destination of trips is positively associated with carpooling (B = 0.67), taking transit (B = 0.26), and non-motorized modes (B = 1.04). Addressing job/population balance at near-destinations, the odds ratios indicate that the probability of carpooling, taking transit, and walking/biking is 1.96, 1.29, and 2.84 times greater, respectively, than driving alone for a 1-unit increase in the log of job/population balance at the near-destination of trips. That means by doubling the job/population balance at the near-destination of trips, the probability of carpooling, taking transit, and walking/biking is 1.59, 1.19, and 2.06 times greater, respectively, than driving alone.

Considering transit availability, the results indicate that a higher transit score significantly decreases the probability of driving alone. The coefficients of transit scores were found to be positive at the origins (*B* = 1.23) and destinations (*B* = 1.11) of trips. The odds ratio indicates that the probability of taking transit is 3.44 times greater than driving alone for a 1-unit increase in the log of the transit score at the origin of trips. Likewise, the probability of walking\biking is 3.03 times greater than driving alone for a 1-unit increase in the log of the transit score at the destination of trips.

The coefficients of walkability scores were found to be positively associated with choosing walking/biking at the origins (*B* = 0.37) and destinations (*B* = 0.53) of trips. The odds ratio indicates that the probability of walking\biking is 1.45 times greater than driving alone for a 1-unit increase in the log of the walk score at the origin of trips. Likewise, the probability of walking\biking is 1.70 times greater than driving alone for a 1-unit increase in the log of the walk score at the destination of trips. These results of the walk score and transit score align with a previous study conducted within Southern California using a subsample of the 2009 National Household Travel Survey (Dillon, 2017).

Effects of Trip Distances on Mode Choice

The signs of trip distance coefficients are negative for carpooling (*B* = -0.13) and non-motorized modes (*B* = -1.92) and positive for taking transit (*B* = 0.74). The odds ratios indicate that the probability of driving alone is 1.14 and 6.8 times greater than carpooling and walking\biking, respectively, for a 1-unit increase in the log of trip distance. The results indicate that non-motorized modes are negatively and strongly associated with trip distance. In other words, increasing trip distance decreases the probability of choosing non-motorized modes. This is because people prefer short trips for choosing non-motorized modes with a distance threshold of 0.5 to 1 mile. The results also indicate that longer trip distances increase the likelihood of choosing public transit when public transit is available. The odds ratio indicates that the probability of taking transit is 2.1 times greater than driving alone for a 1-unit increase in the log of trip distances.

Effects of Traffic Congestion on Mode Choice

Travel time delay, as a measure of traffic congestion, represents the cost imposed upon each commuter’s utility. Based on utility maximization, the more travel time delay between the origin and destination, the less likely that driving alone will be chosen. The present findings also indicate the same relationship. In the full model, travel time delay was found to be significantly and positively associated with carpooling, choosing non-motorized modes, and taking public transit relative to driving alone. The results indicate that travel time delay has a strong effect on carpooling, with a positive coefficient (B = 0.65) at the 95% confidence level. The odds ratio indicates that the probability of carpooling is 1.91 times greater than driving alone for a 1-unit increase in the log of travel time delay. That means by doubling travel time delay, the probability of carpooling is 1.56 times greater than driving alone. This implies that with higher travel time delays, commuters are more likely to share their rides with others.

As expected, higher travel time delays increase the likelihood of taking public transit relative to driving alone. Travel time delay has a strong effect on choosing transit, with a positive coefficient (B = 0.53) at the 95% confidence level. The odds ratio indicates that the probability of taking transit is 1.69 times greater than driving alone for a 1-unit increase in the log of travel time delay. That means by doubling travel time delay, the probability of taking transit is 1.44 times greater than driving alone.

Likewise, travel time delay has a positive effect on the probability of choosing non-motorized modes over driving alone (*B* = 0.79). The odds ratio indicates that the probability of walking\biking is 2.2 times greater than driving alone for a 1-unit increase in the log of travel time delay. That means by doubling travel time delay, the probability of walking\biking is 1.73 times greater than driving alone.

Summary

This chapter provided the results of the VMT and mode choice models developed via SEM and GSEM, respectively. The first section of this chapter described the process of developing the VMT model in the SPSS Amos software package. The results of maximum likelihood estimations and the direct and indirect effects of explanatory variables were discussed in detail. The second section of this chapter presented the process of developing the mode choice model using GSEM in STATA. This section provided details about model validation and interpreted the results of the odds ratios and the probability of choosing each mode of travel.

The next chapter presents the conclusions of the present research, discussing the idea of examining traffic congestion and its effect on travel behavior and providing a summary of policy recommendations and requirements for future studies.

Chapter 6

Conclusions

This research presented a comprehensive framework that investigated the impacts of socioeconomic characteristics, residential self-selection, the built environment, and traffic congestion on VMT and mode choice. Using SEM and GESM techniques, travel behavior was examined with a focus on daily VMT per household and mode choices addressing driving alone, carpooling, taking transit, and non-motorized modes. Analyzing the effects of traffic congestion on VMT and mode choice was the main goal of this study. Scholars have discussed the effects of traffic congestion on greenhouse gas emissions, environmental justice, toxic air exposure, public health, and physical activities. However, among these studies, only a few researchers have considered the effects of congestion on travel behavior (AmoahNyarko, 2014; Bovy & Salomon, 2002; Litman, 2014; Stern et al., 2002).

In the VMT model, SEM was used to investigate VMT per household and its association with socioeconomic factors and built environment factors. The results of the VMT model indicated that both socioeconomic and built environment factors influence daily VMT per household. According to the results, the strongest predictors of VMT—in order of strength—are household size, density score, status of home ownership, and access to free parking at the workplace. Residential preference is another significant factor that affects VMT. The results indicate that density factor is an important variable for explaining household VMT. The findings suggest that doubling density score is associated with a VMT reduction of 21.6 percent. This is consistent with previous studies (Ewing, Tian, & Lyons, 2018; Kim & Brownstone, 2013).

Similarly, the results imply that higher travel time delay is associated with lower VMT per household. In terms of percentage change, the model shows that doubling travel time delay is associated with a 19.9 percent decrease in household VMT. The results of the VMT model suggest that daily VMT is mostly influenced by built environment variables and residential preferences, whereas a mid-term indicator such as vehicle ownership is highly associated with socioeconomic characteristics of households after controlling for self-selection and built environment factors. The results also indicate that vehicle ownership is another factor that increases household daily VMT, though it is dependent on various socioeconomic and built environment factors.

The mode choice model was based on trip-level data and examined the probability of choosing modes of travel, with a focus on driving alone, carpooling, taking transit, and non-motorized modes. Studying PSRC disaggregated data provided an opportunity to examine not only the travel behavior of households or individuals but also to analyze the characteristics of trip origins and destinations. The mode choice model was developed via GSEM with a logit-link function to handle discrete outcomes. The explanatory factors are selected based on relevant theories, previous experimental studies, and model fits. The mode choice model comprises five sub-models that separately investigated the influences of socioeconomic factors, residential preference, and built environment variables on the probability of carpooling, non-motorized trips, and transit usage.

The findings indicate that vehicle availability, residential preference, and transit subsidies strongly influence commuters' travel modes. For example, access to free transit not only increases the probability of taking transit but also increases the likelihood of choosing non-motorized modes relative to driving alone. In contrast, commuters with access to free parking at their workplace have a higher probability of choosing to drive alone over walking\biking or taking transit.

The results also indicate that trip purpose matters. For example, the likelihood of carpooling or taking transit is higher when commuters conduct home-based-work trips.

Regarding built environment factors, the results show that higher activity density and higher job/population balance at the near-origin and near-destination of trips decrease the probability of choosing to drive alone relative to all other modes. The results indicate that the non-motorized mode is highly associated with the distance between a trip's origin and destination. In the full model, travel time delay—as a measure of congestion—was found to be significantly and positively associated with carpooling, taking public transit, or choosing a non-motorized mode relative to driving alone.

Ultimately, the key findings of this study can be summarized as follows:

- Traffic congestion was found to be an influential factor that suppresses VMT per household and encourages commuters to choose carpooling, taking transit, and non-motorized modes of travel.
- Both the origins and destinations of trips are important determinants of travel mode choice. Those within areas with a higher density of activities and job/population balance are less likely to drive alone over all other available modes.
- Strong impacts were found in terms of residential preferences. Holding all other variables constant, those who selected their home location because of access to transit or the walkability of the neighborhood are less likely to drive alone and have a lower daily VMT.

Implications for Policies

The findings of this study can be applied to transportation planning and decision making as tools to reduce VMT and encourage non-motorized modes of travel. The goal of reducing VMT is an official goal of U.S. Government policy, as expressed in the President Clinton's 1993 Climate Change Action Plan (CCAP), in sections of the Clean Air Act (CAA), and in the Congestion Mitigation Air Quality Improvement Program (CMAQ) included in both the Transportation Equity Act for the 21st Century (TEA-21), U.S.C. 23, Section 149 and the Intermodal Surface Transportation Efficiency Act (ISTEA) (Byars, Wei, & Handy, 2017; U.S. Department of Transportation Federal Highway Administration, 2014).

The results of this research present evidence for policies and regulations that are related to land use development, pricing, investments in transit, investments in biking or walking, and travel demand management programs. Increasing density, infill development, and mixed-use development are examples of land use policies that can reduce VMT. The present findings indicate that higher density or increasing land use diversity (job/population balance) reduce daily VMT per household and encourage carpooling or selecting public transit or non-motorized modes. These findings provide some evidence of the importance of shorter distances between origins and destinations in carpooling, transit usage, and non-motorized commuting. This suggests that MPOs and municipalities should consider mixed use developments with more compact communities. This pattern of land use reduces distances between activities and encourages residents to decrease their daily VMT and consider transit or non-motorized modes instead of driving alone. Reducing the distance between origins and destinations is one of the strategies supported by smart growth policies that reduce total VMT in the long-term and facilitate non-motorized modes of travel.

Investments in public transit and walking/biking amenities are other key factors that influence commuters' mode choices. Improving safety, convenience, and network connectivity are useful strategies to increase mobility by alternative modes of transportation. The "complete streets" policy is an example of a policy that can be implemented to provide safe mobility for commuters and encourage them to reduce drive-alone travel and consider other modes. States and local agencies can apply this concept to provide alternative modes of travel by inclusion of facilities for transit vehicles, pedestrians, and bicycles. The results of this research show that higher walkability increases the probability of choosing walking/biking or taking transit relative to driving. Also, the results indicate that households located within areas with greater access to transit have moderately lower daily household VMT.

Increasing the cost of driving—relative to other modes—is another smart growth strategy for reducing VMT. The cost of driving can be influenced by many different factors such as gas price, taxes, parking charges, and travel time delays. While results are preliminary, this research indicates the importance of travel time delay in mitigating VMT and promoting carpooling, taking transit, or choosing non-motorized modes of travel. This is a key point for promoting policies that support increasing the cost of driving and investing in public transit.

It has been argued that developing highways and adding/widening roads is not the only solution to overcoming traffic congestion. In fact, developing highways and freeways causes another issue referred to in economics as "induced demand" (de Dios Ortúzar & Willumsen, 2011). This concept suggests that developing new roads and increasing road capacity encourages auto dependency and spreading activities throughout low density suburbs. In contrast, it has been argued that investment in public transit and congestion pricing may better address traffic congestion; not only does it provide more reliable and sustainable means of transportation, but it also encourages people in the long run to consider carpooling or taking transit instead of driving alone.

Transportation demand management (TDM) programs can be implemented to reduce VMT and encourage commuters to choose options other than driving alone. TDM includes a variety of strategies such as telecommuting programs, parking management, and employer-based trip reduction (EBTR) programs. The results of this research indicate that households with access to free parking have higher daily VMT. This finding provides evidence for TDM to develop a Public-Private Partnership (P3) to encourage the use of public transit or participate in carpooling programs.

Research Advantages and Limitations

This research presents results on how traffic congestion influences travel behavior. The methodology of this research offers several advantages. First, it presents the process of quantifying traffic congestion at a sub-area level and developing a “delay score” as the additional “D” factor in travel behavior studies. Using time-related mobility measures at a local level can help planners and decision-makers uncover the interrelationships between congestion and factors such as VMT, trip frequency, mode choice, route choice, and other travel behavior outcomes. In addition to transportation planning studies, a time-related mobility measure such as travel time delay can be used in public health studies to examine the effects of higher travel time delays on physical activity, obesity, and other health-related factors.

In this study, the delay score was calculated using the Google Maps Distance Matrix API. With this computation, the implemented methodology can be used in other fields/analyses such as public health and travel demand modeling. Another advantage of this study was conducting the analysis at the household level and trip level with built environment factors at near-origins and near-destinations. Using disaggregated household travel survey data provides a key contribution to the literature by exploring individuals' mobility patterns and improves the process of understanding travel behavior without the problem of aggregation bias.

There are also some limitations of the present research that should be addressed. Due to the nature of the research questions and the availability of GPS-based travel survey data, this research was limited to analyzing data from the Seattle metropolitan area. This research was conducted prior to 2017 NHTS data being published at the disaggregated level. Analyzing disaggregated data at the national level could enhance our understanding of traffic congestion and its impact on travel behavior.

This research examined travel behavior in the context of VMT and mode choice while other aspects, such as route choice and destination choice, were not explored. Route choice and destination choice analyses require specific data that were not gathered in the PSRC travel survey program. Ultimately, this research used cross-sectional travel survey data gathered in 2015. Applying panel data or longitudinal travel survey data would improve our understanding of travel behavior and the effects of congestion between two time periods.

The limitations of this study point towards topics to be considered in future research. The following topics are a few potential areas for future research:

- How does traffic congestion between home and work influence commuters' departure times, their route choices, and the distance to work?
- How does relocating (job or residential) affect mode of travel when travel time delay between home and work is decreased or increased?
- How does travel time delay influence health-related factors such as physical activity or obesity?

Appendix A

Transportation Performance Measures

Definitions of Transportation Performance Measures

The **travel time** (in minutes) is the time needed to complete a trip and move from the origin to the destination. There are different ways to measure travel time. For example, it can be calculated directly using archived data from official traffic management agencies or by conducting field survey studies. Also, it can be calculated using empirical relationships with roadway characteristics and traffic volume, validated travel demand models, or the projected effects of improvements (Schrank et al., 2005).

The **peak-hour period** (rush hour) can be defined as follows:

> …part of the day during which traffic congestion on roads and crowding on public transport is at its highest. Normally, this happens twice every weekday—once in the morning and once in the afternoon or evening, the times during which the most people commute (Wikipedia).

According to Schrank et al. (2005), historical traffic count data such as annual average daily traffic (AADT) and average daily traffic (ADT) cannot be used to calculate the travel time index (TTI) or the Buffer Index. Using daily traffic volume data in the TTI is not meaningful because the measure is meant to compare off-peak and peak travel conditions, whereas ADT data cannot provide these details.

Total delay (in person- or vehicle-hours) is the total extra time wasted due to traffic congestion. The total delay can be considered for both transit and roadway segments. According to Schrank et al. (2005), “delay” can be quantified as a ratio of actual travel time to the free-flow or posted speed limit. Equation A-1 presents the calculation of delay in person-hours. In addition to the total delay, the delay per person or delay per peak period traveler can be calculated by daily minutes or annual hours, which is easily interpretable for non-technical audiences.

$$\underset{(person - hours)}{Total\ Delay} = \tag{A-1}$$

$$\left[\begin{matrix} Actual \\ \text{Travel Time} \\ (minutes) \end{matrix} - \begin{matrix} FFS\ or\ PSL \\ \text{Travel Time} \\ (minutes) \end{matrix}\right] \times \underset{(vehicles)}{Vehicle\ Volume} \times \underset{(vehicles)}{Vehicle\ Occupancy} \times \frac{1\ hour}{60\ minutes}$$

The **total delay in an urban area or a corridor** is calculated as the total of individual segment delays (Schrank et al., 2005). The aggregated total delay within urban areas can be used by transportation planning agencies to evaluate the impact of major highway improvements on transportation systems and provides useful information for economic or benefit/cost analyses.

The **Travel Time Index (TTI)** is a dimensionless measure that presents the ratio of peak-period travel time to free-flow travel time. The TTI implies commuters' perceptions of travel time on the roadway. This indicator presents the length of extra time wasted during a trip in the transportation system. For example, a TTI of 1.3 means that a trip that takes 30 minutes during the off-peak period will be 30 percent longer and will take 39 minutes during the peak period.

New technologies in traffic congestion have enhanced the estimation of the TTI. Texas A&M Transportation Institute changed the methodology of calculating TTI in 2015. Equation A-2 presents the previous formula for the TTI. In the previous method, time periods were weighted by VMT using volume estimates derived from FHWA's Highway Performance Monitoring System (HPMS).

$$\text{Travel Time Index} = \frac{\left[\frac{\text{Freeway Travel Rate}}{\text{Freeway Free-flow or Posted Speed Limit Rate}} \times \text{Freeway Peak Period VMT}\right] + \left[\frac{\text{Principal Arterial Street Travel Rate}}{\text{Principal Arterial Street Free-flow or Posted Speed Limit Rate}} \times \text{Principal Arterial Street Peak Period VMT}\right]}{\text{Freeway Peak Period VMT} + \text{Principal Arterial Street Peak Period VMT}} \tag{A-2}$$

The current methodology for calculating the TTI is based on travel time (Equation A-3 and A-4). According to FHWA, this measure is calculated for the AM peak period (6 am to 9 am) and PM peak period (4 pm to 7 pm) on weekdays.[3]

$$\text{Travel Time Index} = \frac{\text{Peak Travel Time}}{\text{Off Peak Travel Time}} \tag{A-3}$$

$$\text{Travel Time Index} = \frac{\text{Delay Time} + \text{Free Flow Travel Time}}{\text{Free Flow Travel Time}} \tag{A-4}$$

The **Travel Rate Index (TRI)** is a dimensionless measure, similar to the TTI, that compares traffic conditions during the peak period to traffic conditions during free-flow or posted speed limit conditions. The difference between TRI and TTI is the implementation of traffic incident data. Traffic incidents are not considered in the TRI, whereas the TTI considers the effects of incidents on travel time using continuous traffic count data streams.

The **Buffer Index (BI)** implies trip reliability, indicating the amount of extra “buffer” time required to be on time for 95 percent of trips. For example, this index provides an estimate of extra time needed to avoid being late for work one day per month. The index can be explained as “a traveler should allow an extra BI percent travel time due to variations in the amount of

[3] https://ops.fhwa.dot.gov/perf_measurement/ucr/documentation.htm

congestion delay on that trip" (Schrank et al., 2005, p. 30). According to Schrank et al. (2005), the BI and delay measures could also be beneficial in the off-peak period within locations with a higher density of traffic or congestion during off-peak hours.

With continuous data, the BI creates a time- and distance-neutral measure estimated for each road or transit route segment. According to Schrank et al. (2005), a weighted average of BI can be estimated using VMT or PMT as a weighting factor. Schrank et al. (2005) stated that travel rates for approximately 5-mile sections of roadway provide reliable data to measure congestion for a corridor or sub-area. BI can also be aggregated for a sub-area by implementing a weighted average for more than one roadway and using VMT or PMT on each roadway section. To calculate the BI within a region, the actual minute values could be obtained from an individual traveler for a particular trip length or specific origin-destination pair within 5-mile buffers. Equation A-5 presents the calculation of the BI, which can be implemented for each road segment or particular system element.

$$Buffer\ Index\ (\%) = \left[\frac{\begin{matrix} 95\,th \\ Percentile\ \text{Travel Time} \\ (minutes) \end{matrix} - \begin{matrix} Average \\ \text{Travel Time} \\ (minutes) \end{matrix}}{\begin{matrix} Average\ Travel\ Time \\ (minutes) \end{matrix}}\right] \times 100\% \tag{A-5}$$

According to Schrank et al. (2005), the buffer time concept provides basic information for travelers to make decisions. Schrank et al. (2005) listed different questions which commuters consider when making a trip. These questions include, "When should I leave?", "How far is it?", "When do I need to arrive?", "How much time do I need to allow?", and "How bad is the traffic?", among others. Conceptually, considering the level of traffic congestion and extra time required to spend on the transportation system, commuters will have different reactions. Based on the extra time that has to be allowed for uncertainty in travel conditions, travelers make different decisions based on their "time allowance" stage and other socioeconomic factors.

Traffic congestion and the extra time of travel could be related to various factors such as weather, incidents, holidays or special events, construction zones, or other traffic irregularities (Schrank et al., 2005)

Congested Travel is a measure that represents the total level of congested roads within a geographic area. It quantifies the sum of the congested corridor that is influenced by the high level of traffic volumes. Equation A-6 illustrates the calculation of congested travel in vehicle-miles as the product of the congested segment length and the vehicle volume summed across all congested segments (Schrank et al., 2005).

$$\begin{matrix} Congested\ Travel \\ (vehicle-miles) \end{matrix} = \sum \left[\begin{matrix} Congested \\ \text{Segment Length} \\ (miles) \end{matrix} \times \begin{matrix} Vehicle \\ \text{Volume} \\ (vehicles) \end{matrix} \right] \tag{A-6}$$

The **Percent of Congested Travel** is similar to congested travel, but this measure considers more factors—such as speed and occupancy data—to estimate the extent of congestion. It is calculated as the ratio of the congested segment person-hours of travel to the total person-hours of travel. Equation A-7 illustrates the calculation of the percent of congested travel (Schrank et al., 2005).

$$Percent\ of\ Congested\ Travel = \tag{A-7}$$

$$= \left[\frac{\displaystyle\sum_{i=1}^{m} \left(\left(\begin{matrix} Actual \\ Travel \\ Time_i \\ (minutes) \end{matrix} - \begin{matrix} FFS\ or\ PSL \\ Travel \\ Time_i \\ (minutes) \end{matrix} \right) \times \left(\begin{matrix} Vehicle \\ Volume_i \\ (vehicles) \end{matrix} \times \begin{matrix} Vehicle \\ Occupancy_i \\ (persons/vehicle) \end{matrix} \right) \right)_{Each\ congested\ segment}}{\displaystyle\sum_{i=1}^{n} \left(\begin{matrix} Actual\ Travel\ Rate_i \\ (minutes\ per\ mile) \end{matrix} \times \begin{matrix} Length_i \\ (miles) \end{matrix} \times \begin{matrix} Vehicle \\ Volume_i \\ (vehicles) \end{matrix} \times \begin{matrix} Vehicle \\ Occupancy_i \\ (persons/vehicle) \end{matrix} \right)_{All\ segments}} \right] \times 100$$

Congested Roadway is another transportation performance measure that calculates the extent of congestion within a region. It is the sum of the mileage of roadways that operate under free-flow or posted speed limit conditions. This is shown in Equation A-8 (Schrank et al., 2005).

$$\begin{array}{c} Congested\ Roadway \\ (miles) \end{array} = \begin{array}{c} \Sigma\ Congested\ Segment \\ Length\ (miles) \end{array} \tag{A-8}$$

According to the Urban Mobility Report, the VOC ratio can be used to calculate the total mileage of congested roads. This ratio is often used as a measure of the sufficiency of existing or proposed capacity. The VOC ratios for each segment can be calculated by dividing the volume by the capacity using FHWA's HPMS dataset and the HCM. Additionally, the volume and network inventory data from HPMS geospatial GIS files can be used to calculate VMT and VMT per lane-mile, which indicates the traffic density.

The **Road Congestion Index (RCI)** is transportation performance measure that represents a higher level of traffic congestion if the index value is greater than or equal to 1.0. Using the average capacity of highways and principal arterials, Equation A-9 presents the formula for calculating the RCI. The resulting ratio presents a higher level of congestion if the index value is greater than or equal to 1.0.

$$Road\ Congestion\ Index = \tag{A-9}$$

$$\frac{Prin.Arterial\ VMT\ (per\ ln.mi) \times Prin.Arterial\ VMT + Freeways\ VMT\ (per\ ln.mi) \times Freeway\ VMT}{5{,}000 \times Prin.Arterial\ VMT + 14{,}000 \times Highways\ VMT}$$

Accessibility is another transportation performance measure that often represents mobility measures. It examines how many different opportunities can be reached during different times of the day. In addition to job accessibility, the "opportunity" can refer to accessibility to a transit station or other activities of interest. Accessibility is satisfied if the travel time to perform the desired activity is less than or equal to the target travel time, as indicated in Equation A-10.

(A-10)

$$Accessibility\ (opportunities) = \Sigma\ Objective\ Fullfillment\ Opportunities\ \textit{(e.g., jobs), Where}\ \textit{Travel Times} \leq \textit{Target Travel Time}$$

Appendix B

PSRC Household Travel Survey Program

Puget Sound Travel Survey Program

Example of Questions in 2015 Travel Survey Program[1]:

1. Please tell us about the vehicles in your household: Year, Make, Model, Fuel type. Does this vehicle have a disability license plate or parking pass? When did your household purchase/obtain this vehicle?
2. How many total people (including yourself) currently live in your household?
3. Please tell us about yourself.
    - Initials or nickname;
    - Gender;
    - Age;
    - Primary type of employment [if employed full/part/self];
    - Number of jobs;
    - Highest level of education completed;
    - Has a valid driver's license;
    - Vehicle used most often; Currently a student?
    - How often typically travels on a toll road or toll bridge in the Puget Sound Region?
    - Adult: Student status
    - Household size
    - Number of adults in household age 18+ (derived)
    - Number of children in household under 18 (derived)
    - Number of workers in household
4. How many motor vehicles (in working order) are there in your household?
5. How many months of the year do you live at your current residence (the residence where we sent your invitation to participate in this study)?
6. How long have you lived at your current residence?
7. Do you rent or own your current residence?
8. What type of place is your current residence?
9. How important were each of these factors when choosing to move to where you live now:
    - A change in family size or marital/partner status

[1] Source: https://www.psrc.org/travel-surveys-2015-household-survey

- Affordability
- Quality of schools (K-12)
- Having a walkable neighborhood and being near local activities
- Having space & separation from others
- Being close to family or friends
- Being close to public transit Being close to the highway
- Being within a 30-minute commute to work

10. Please share where your home is located.
11. In 2014, what was your household's total annual income (from all sources) before taxes or other deductions from pay?
12. What type and model of smartphone do members of your household have?
13. Number of trips made on travel day (derived)
14. Where started\ ended (travel day)
15. Transit Subsidy: Employer or school pays for part or all of transit pass or E-purse value
16. Work: How often commute to primary workplace
    - If commutes: Typical commute mode
17. Work benefit:
    - Flextime (can adjust schedule as long as work the right number of total hours)
    - Free or subsidized parking
    - Free or subsidized transit use
18. Main purpose of trip (derived)
19. Travel Mode: Main way traveled on trip
20. Total number of travelers on trip including self (derived)
21. Car, motorcycle or vanpool: Vehicle used on trip
22. Transit: Access\ Egress mode: Walked or jogged; Rode a bike; Drove and parked a car (e.g. a vehicle in my household); Drove and parked a carshare vehicle (e.g. ZipCar, Car2Go); Got dropped off; Got picked up; Took a taxi (e.g. Yellow Cab, Lyft)

Appendix C:

Walk Score and Transit Score API

API Parameters and Requirements

The Walk Score and Transit Score APIs from the Walk Score website (walkscore.com) allow users to obtain information about the walkability and access to public transit for places in the U.S and other countries. The Walk Score measures the walkability of places and the Transit Score measures access to public transit. This API returns the value of the Walk Score and Transit Score rated from 0 to 100. The higher value indicates more pedestrian friendliness or better access to public transit within a walkable distance (Kocher & Lerner, 2018). Table C- 1 presents the list of required and optional parameters in the API.

Table C- 1. List of Parameters in the Walk Score and Transit Score APIs

Parameter	Description	Required
Walk Score		
lat	The latitude of the requested location.	Yes
lon	The longitude of the requested location.	Yes
address	The URL encoded address.	Yes
wsapikey	Your Walk Score API Key.	Yes
transit	Set transit=1 to request Transit Score (if available).	No
bike	Set bike=1 to request Bike Score (if available).	No
format	Return results in XML or JSON (defaults to XML).	No
Transit Score		
lat	The latitude to score.	Yes
lon	The longitude to score.	Yes
city	The name of the city where the address is located.	Yes
state	A two-letter USPS state code for the city. You must supply this parameter for cities in the United States; for all other cities, you should instead use the country parameter.	Yes
country	A two-letter ISO-3166 country code for the city. You must supply this parameter for cities outside of the United States; for cities in the United States, use the state parameter instead.	No
research	If yes, the Transit API bypasses validating the city, state, and country parameters. When set to yes, transit scores are considered experimental.	No

Source: Kocher & Lerner, 2018

The result of API calls and their descriptions are shown in Table C- 2.

Table C- 2. List of The API returns

Result	Description
Walk Score	
status	Status code of the result (see information below).
walkscore	The Walk Score of the location.
description	An English description of the Walk Score. e.g., Somewhat Walkable.
updated	When the Walk Score was calculated.
logo_url	Link to the Walk Score logo.
more_info_icon	Link to question mark icon to display next to the score.
more_info_link	URL for the question mark to link to.
ws_link	A link to the walkscore.com score and map for the point.
help_link	A link to the "How Walk Score Works" page.
snapped_lat	All points are "snapped" to a grid (roughly 500 feet wide per grid cell). This value is the snapped latitude for the point.
snapped_lon	The snapped longitude for the point.
Transit Score	
transit_score	The score, an integer between 0 and 100 inclusive.
description	An English description of the Transit Score suitable for display to users. e.g., Rider's Paradise.
summary	An English summary of the number of routes used to compute this transit score.
ws_link	A link to the Transit Score page for this address on walkscore.com.
logo_url	Link to the Walk Score logo.
help_link	A link to the walkscore.com page for how scoring works.

Source: Kocher & Lerner, 2018

API Calls with R Package

In this study, the R programming was utilized to obtain the Walk Score and Transit Score from the API. R provides a collection of functions to perform API calls associated with the Walk Score website (www.walkscore.com). These functions can be used to query the Walk Score and Transit Score database for a wide variety of information using R scripts (Whalen, 2015). Every function in R package requires the use of a Walk Score API key number, entered as a parameter. The key is free to obtain with limited use and can be requested here: http://www.walkscore.com/professional/api.php. The easiest way to enter the key is to store the string as a variable and enter that variable as a parameter for the function calls (Whalen, 2015).

Walk Score API Call

getWS: A function to perform the basic Walk Score API call.

Usage: getWS(x, y, key)

Arguments:

x	longitude of query location (numeric)
y	latitude of query location (numeric)
key	Walk Score API key (string)

Value:

Returns an object of class WalkScore, basically a list of the following elements:

status	Status code of the request. Status of 1 indicates a successful call. See the Walk Score API page for interpretation of other codes.
walkscore	Walk Score of query location.
description	Qualitative description of location.
updated	Date and time of most recent update to this location's Walk Score.
snappedLong	grid point longitude to which the input was snapped to.
snappedLat	grid point latitude to which the input was snapped to.

Example: getWS(-73.98496,40.74807,"your key")

Transit Score API Call

getTS: A function to perform the basic Transit Score API call.

Usage: getTS(x, y, city, state, key)

Arguments:

x	longitude of query location (numeric)
y	latitude of query location (numeric)
city	name of core city where the query location is located (string)
state	postal abbreviation of query location's state (string)
key	Walk Score API key (string)

Value:

Returns an object of class TransitScore, basically a list of the following elements:

transitscore	Transit Score of query location
url	Link to Walk Score page associated with your query.
description	Qualitative description of query location regarding transit.
summary	Summary of nearby routes and stops.

Example: getTS(-73.98496,40.74807,"New York","NY","your key")

Appendix D

The Google Distance Matrix API

API Parameters and Requirements

The Distance Matrix API is a service from Google Maps that provides travel distance and time for a matrix of origins and destinations.[5] The API returns travel time and distance information that consists of rows containing duration and distance values for each O-D pair (Google LLC, 2018). Table D- 1 presents the list of parameters in the Distance Matrix API.

Table D- 1. List of Parameters in The Distance Matrix API

Parameter	Description
Required	
origins	The starting point for calculating travel distance and time.
Destinations	One or more locations to use as the finishing point for calculating travel distance and time.
key	The application's API key. This key identifies your application for purposes of quota management.
Optional	
mode	Driving (default) indicates distance calculation using the road network. Walking requests distance calculation for walking via pedestrian paths & sidewalks (where available). Bicycling requests distance calculation for bicycling via bicycle paths & preferred streets (where available).
language	The language in which to return results.
region	The region code, specified as a ccTLD (country code top-level domain) two-character value.
avoid	The following restrictions are supported: avoid=tolls; avoid=highways; avoid=ferries; avoid=indoor
units	units=metric (default) returns distances in kilometers and meters. units=imperial returns distances in miles and feet.
arrival_time	Specifies the desired time of arrival for transit requests, in seconds since midnight, January 1, 1970 UTC.
departure_time	The desired time of departure. You can specify the time as an integer in seconds since midnight, January 1, 1970 UTC.
traffic_model	best_guess (default), pessimistic, and optimistic.
transit_mode	Bus; subway; train; tram (light rail); rail

Source: The Google Maps API

[5] https://developers.google.com/maps/documentation/distance-matrix/intro

API Calls with R Package

In this study, R programming software was utilized to obtain Google travel times and calculate travel time delays. The R function gmapsdistance uses the Google Maps Distance Matrix API in order to compute the distance(s) and time(s) between two points (Melo, Rodriguez, & Zarruk, 2018). In order to be able to use the function, users will need an API key and enable the Distance Matrix API in the Google Developers Console. The R function ‘gmapsdistance’ provides distance and travel time between two points from Google Maps, including four possible modes of transportation: bicycling, walking, driving and public transportation (Melo et al., 2018).

Table D- 2. List of Arguments in the R Package ‘gmapsdistance’

Arguments	Description
origin	A string or vector of strings containing the description of the starting point(s).
destination	A string or vector of strings containing the description of the end point(s).
mode	A string containing the mode of transportation desired. Should be inside of double quotes (",") and one of the following: "bicycling", "walking", "transit" or "driving".
key	In order to use the Google Maps Distance Matrix API it is necessary to have an API key
avoid	When the mode is set to "driving", the user can find the time and distance of the route by avoiding tolls, highways, indoor and ferries
departure	The time and distance can be computed at the desired time of departure.
dep_date	Instead of using the departure option, the user can set the departure date and time using dep_date and dep_time options
dep_time	Instead of using the departure option, the user can set the departure date and time using dep_date and dep_time options.
traffic_model	When the mode is set to "driving", the user can find the times and distances using different traffic models. Should be a string and one of the following: "optimistic", "pessimistic", "best_guess" or "None" (default).
arrival	The time and distance can be computed to arrive at a predetermined time.
arr_date	Instead of using the arrival option, the user can set the arrival date and time using arr_date and arr_time options.
arr_time	Instead of using the arrival option, the user can set the arrival date and time using arr_date and arr_time options. The user cannot input both departure and arrival times

Source: Melo, Rodriguez, & Zarruk, 2018

Appendix E

Mode Choice Results

Table E- 1. Comparison of Logit Models and Probability of Carpooling Mode Relative to Drive Alone Mode of Travel

Model Specifications	Model 1 exp(b)	Model 2 exp(b)	Model 3 exp(b)	Model 4 exp(b)	Model 5 exp(b)
	Base	Res. Preference	Trip Purpose	Built Environment	Travel Time Delay
Mode 1: Drive Alone (base outcome)					
Mode 2: Carpooling					
age	0.924***	0.923***	0.905***	0.973	0.987
male	1.090**	1.089**	0.996	1.014	1.020
education	0.946***	0.946***	0.935***	0.874***	0.869
hh_size	1.647***	1.643***	1.660***	2.195***	2.245***
hh_workers	0.669***	0.669***	0.745***	0.568***	0.540***
hh_income	1.071**	1.074**	1.045	0.957	0.951
hh_vehicles	0.884***	0.884***	0.852***	1.365***	1.380***
access_free_transit	1.615***	1.604***	1.775***	0.973	0.969
access_free_parking	0.586***	0.590***	0.677***	0.853**	0.863**
res_factors_hwy	n/a	0.991	0.995	0.977	0.972
tp_hbw	n/a	n/a	0.1591***	0.100***	0.092***
tp_shop	n/a	n/a	0.811***	0.878*	0.932
tp_nhb	n/a	n/a	1.009	0.603***	0.582***
tp_socrec	n/a	n/a	1.727***	2.008***	2.105***
density_origin	n/a	n/a	n/a	1.928***	1.818***
density_destin	n/a	n/a	n/a	2.414***	2.160***
jobpop_origin	n/a	n/a	n/a	1.314***	1.315***
jobpop_destin	n/a	n/a	n/a	1.926***	1.955***
distance_od	n/a	n/a	n/a	1.440***	0.874**
delay_od	n/a	n/a	n/a	n/a	1.906***
_cons	0.679	0.693	1.074	0.0239***	0.041***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. n/a means parameter not estimated in the model.

Table E- 2. Comparison of Logit Models and Probability of Taking Transit Mode Relative to Drive Alone Mode of Travel

Model Specifications	Model 1 exp(b)	Model 2 exp(b)	Model 3 exp(b)	Model 4 exp(b)	Model 5 exp(b)
	Base	Res. Preference	Trip Purpose	Built Environment	Travel Time Delay
Mode 1: Drive Alone (base outcome)					
Mode 3: Transit (bus\train)					
age	0.916***	0.930***	0.972	1.022	1.036
male	0.867**	0.856**	0.881*	1.113	1.115
education	0.931***	0.918***	0.902***	0.735***	0.730***
hh_size	1.033	1.028	1.083*	1.748***	1.788***
hh_workers	1.392***	1.313**	1.151**	0.694***	0.664***
hh_income	0.925	0.924	0.879**	0.674***	0.674***
hh_vehicles	0.252***	0.319***	0.305***	0.553***	0.554***
access_free_transit	9.235***	8.147***	7.782***	3.494***	3.468***
access_free_parking	0.127***	0.129***	0.111***	0.197***	0.2017***
res_factors_transit	n/a	1.539***	1.583***	1.277***	1.276***
tp_hbw	n/a	n/a	2.336***	0.537***	0.507***
tp_shop	n/a	n/a	0.488	0.680***	0.717**
tp_nhb	n/a	n/a	1.071	0.471***	0.453***
tp_socrec	n/a	n/a	1.054	1.249*	1.300*
density_origin	n/a	n/a	n/a	2.529***	2.421***
density_destin	n/a	n/a	n/a	2.568***	2.363***
jobpop_origin	n/a	n/a	n/a	1.444***	1.453***
jobpop_destin	n/a	n/a	n/a	1.273***	1.294***
transitscore_origin	n/a	n/a	n/a	3.397***	3.435***
transitscore_destin	n/a	n/a	n/a	3.128***	3.026***
distance_od	n/a	n/a	n/a	3.167***	2.101***
delay_od	n/a	n/a	n/a	n/a	1.690***
_cons	4.047**	0.621	0.812	0.00***	0.00***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. n/a means parameter not estimated in the model.

Table E- 3. Comparison of Logit Models and Probability of Choosing Non-Motorized Mode Relative to Drive Alone Mode of Travel

Model Specifications	Model 1 exp(b)	Model 2 exp(b)	Model 3 exp(b)	Model 4 exp(b)	Model 5 exp(b)
	Base	Res. Preference	Trip Purpose	Built Environment	Travel Time Delay
Mode 1: Drive Alone (base outcome)					
4.Mode: Non-Motorized (walking\biking)					
age	0.853***	0.859***	0.845***	0.933**	0.947*
male	0.836***	0.829***	0.780***	0.656***	0.667***
education	1.081***	1.065***	1.039**	0.973	0.968
hh_size	0.986	0.997	1.042	1.464***	1.499***
hh_workers	1.151***	1.125***	1.230***	0.785***	0.745***
hh_income	1.023	0.982	0.938*	0.939	0.945
hh_vehicles	0.4176***	0.463***	0.438***	1.077	1.085
access_free_transit	3.106***	3.193***	3.473***	1.911***	1.862***
access_free_parking	0.340***	0.335***	0.362***	0.570***	0.589***
res_factors_walk	n/a	1.438***	1.446***	1.124***	1.127***
tp_hbw	n/a	n/a	0.451***	0.937	0.858
tp_shop	n/a	n/a	0.728***	0.429***	0.457***
tp_nhb	n/a	n/a	0.799***	0.299***	0.286***
tp_socrec	n/a	n/a	3.922***	4.511***	4.638***
density_origin	n/a	n/a	n/a	2.290***	2.104***
density_destin	n/a	n/a	n/a	2.364***	2.052***
jobpop_origin	n/a	n/a	n/a	1.289***	1.275***
jobpop_destin	n/a	n/a	n/a	2.775***	2.843***
walkscore_origin	n/a	n/a	n/a	1.356***	1.447***
walkscore_destin	n/a	n/a	n/a	1.598***	1.697***
distance_od	n/a	n/a	n/a	0.256***	0.146***
delay_od	n/a	n/a	n/a	n/a	2.203***
_cons	3.362***	1.039	1.391	0.001***	0.001***

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. n/a means parameter not estimated in the model.

References

Adams, J. F. (1973). *Human behavior in a changing society*. Boston, MA: Holbrook Press.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2011). The theory of planned behaviour: Reactions and reflections. *Psychology & Health*, *26*(9), 1113–1127. https://doi.org/10.1080/08870446.2011.613995

Ajzen, I., Heilbroner, R. L., Fishbein, M., & Thurow, L. C. (1980). *Understanding attitudes and predicting social behaviour*. Upper Saddle River, NJ: Prentice Hall.

Alexander, J. C. (1982). *Positivism, presuppositions, and current controversies* (Vol. 1). Oakland, CA: University of California Press.

Allport, G. W. (1966). Traits revisited. *American Psychologist*, *21*(1), 1–10. https://doi.org/10.1037/h0023295

Alonso, W. (1964). *Location and land use, toward a general theory of land rent*. Boston, MA: Harvard University Press. https://doi.org/10.4159/harvard.9780674730854

AmoahNyarko, R. (2014). *The causes and effects of traffic jam on commercial transport operations. A case study of Trotro drivers at Awutu Senya East municipality* (Master's thesis). University of Ghana, Accra, Ghana.

Anas, A., Arnott, R., & Small, K. A. (1998). Urban spatial structure. *Journal of Economic Literature*, *36*(3), 1426–1464.

Anderson, W., Kanaroglou, P., & Miller, E. (1996). Urban form, energy and the environment: A review of issues, evidence and policy. *Urban Studies*, *33*(1), 7–35. https://doi.org/10.1080/00420989650012095

Arbuckle, J. L. (2009). *IBM SPSS Amos 19 user's guide*. Chicago, IL: SPSS Inc.

Archer, M. S. (2000). *Being human: The problem of agency*. Cambridge: Cambridge University Press.

Bagley, M. N., & Mokhtarian, P. L. (2002). The impact of residential neighborhood type on travel behavior: A structural equations modeling approach. *The Annals of Regional Science*, *36*(2), 279–297. https://doi.org/10.1007/s001680200083

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall, Inc.

Basarić, V., Vujičić, A., Simić, J. M., Bogdanović, V., & Saulić, N. (2016). Gender and age differences in the travel behavior – A Novi Sad case study. *Transportation Research Procedia*, *14*, 4324–4333. https://doi.org/10.1016/j.trpro.2016.05.354

Baum, C. (2016). *Introduction to Generalized Structural Equation Modeling (GSEM) in Stata*. Boston College, Newton, Massachusetts.

Beige, S., & Axhausen, K. W. (2017). The dynamics of commuting over the life course: Swiss experiences. *Transportation Research Part A: Policy and Practice*, *104*, 179–194. https://doi.org/10.1016/j.tra.2017.01.015

Ben-Akiva, M., & Bierlaire, M. (2003). Discrete choice models with applications to departure time and route choice. In R. W. Hall (Ed.), *Handbook of Transportation Science. International Series in Operations Research & Management Science* (Vol. 56, pp. 7–37). Boston, MA: Springer.

Ben-Akiva, M., & Lerman, S. R. (1985). *Discrete choice analysis: Theory and application to travel demand* (Vol. 9). Cambridge, MA: MIT press.

Bentler, P. M. (1985). *Theory and implementation of EQS: A structural equations program*. Los Angeles, CA: BMDP Statistical Software.

Bentler, P. M. (1995). *EQS structural equations program manual*. Encino, CA: Multivariate Software.

Bentler, P. M., & Hu, L. T. (1995). Evaluating model fit. In R. H. Hoyle (Ed.), *Structural Equation Modeling: Concepts, Issues, and Applications* (pp. 76–99). Thousand Oaks, CA: Sage Publications, Inc.

Bento, A. M., Cropper, M. L., Mobarak, A. M., & Vinha, K. (2005). The effects of urban spatial structure on travel demand in the United States. *Review of*

Economics and Statistics, *87*(3), 466–478. https://doi.org/10.1162/0034653054638292

Bhaskar, R. (1989). *The possibility of naturalism: A philosophical critique of the contemporary human sciences* (1st ed.). Hassocks: Harvester Press.

Bhat, C. R., & Guo, J. Y. (2007). A comprehensive analysis of built environment characteristics on household residential choice and auto ownership levels. *Transportation Research Part B: Methodological*, *41*(5), 506–526. https://doi.org/10.1016/j.trb.2005.12.005

Bhiromkaew, J. (2006). *Examining the effects of transit service on commuting mode choice and residential location choice* (Doctoral dissertation). Portland State University, Portland, OR.

Blumen, O. (1994). Gender differences in the journey to work. *Urban Geography*, *15*(3), 223–245. https://doi.org/10.2747/0272-3638.15.3.223

Boarnet, M. (2011). A broader context for land use and travel behavior, and a research agenda. *Journal of the American Planning Association*, *77*(3), 197–213. https://doi.org/10.1080/01944363.2011.593483

Boarnet, M., & Crane, R. (2001). *Travel by design: The influence of urban form on travel*. Oxford, United Kingdom: Oxford University Press.

Boarnet, M., & Greenwald, M. (2000). Land use, urban design, and nonwork travel: Reproducing other urban areas' empirical test results in Portland, Oregon. *Transportation Research Record: Journal of the Transportation Research Board*, *1722*, 27–37. https://doi.org/10.3141/1722-04

Boarnet, M., Kim, E., & Parkany, E. (1998). Measuring traffic congestion. *Transportation Research Record: Journal of the Transportation Research Board*, (1634), 93–99.

Boarnet, M., Nesamani, K., & Smith, S. (2003). Comparing the influence of land use on nonwork trip generation and vehicle distance traveled: An analysis using travel diary data.

Boarnet, M., & Sarmiento, S. (1998). Can land-use policy really affect travel behaviour? A study of the link between non-work travel and land-use characteristics. *Urban Studies*, *35*(7), 1155–1169. https://doi.org/10.1080/0042098984538

Bohte, W., Maat, K., & Wee, B. van. (2007). Residential self-selection. the effect of travel-related attitudes and lifestyle orientation on residential location choice; evidence from the Netherlands. Presented at the 11th World Conference on Transport Research, Berkeley CA: TRID. Retrieved from https://trid.trb.org/view/884684

Bollen, K. A. (1989). *Structural equations with latent variables*. New York, NY: Wiley.

Bovy, P. H., & Salomon, I. (2002). Congestion in Europe: Measurements, patterns and policies. In E. Stern, I. Salomon, & P. H. L. Bovy (Eds.), *Travel Behaviour: Spatial Patterns, Congestion and Modelling* (pp. 143–179). Cheltenham, United Kingdom: Edward Elgar Publishing.

Brinkman, J. C. (2016). Congestion, agglomeration, and the structure of cities. *Journal of Urban Economics*, *94*, 13–31. https://doi.org/10.1016/j.jue.2016.05.002

Brownstone, D., & Golob, T. (2009). The impact of residential density on vehicle usage and energy consumption. *Journal of Urban Economics, 65*(1), 91–98.

Brueckner, J. K. (2000). Urban sprawl: Diagnosis and remedies. *International Regional Science Review*, *23*(2), 160–171. https://doi.org/10.1177/016001700761012710

Byars, M., Wei, Y., & Handy, S. (2017). *State-level strategies for reducing vehicle miles of travel*. University of California, Davis: Institute for Transportation Studies.

Cambridge Systematics, Inc. (2005). *Traffic congestion and reliability: Trends and advanced strategies for congestion* (Final Report). Cambridge, MA: U.S Department of Transportation - Federal Highway Administration (FHWA).

Cao, X., Mokhtarian, P., & Handy, S. (2009). Examining the impacts of residential self-selection on travel behaviour: A focus on empirical findings, 359–395.

Cattell, R. B. (1966). Patterns of change: Measurement in relation to state dimension, trait change, lability, and process concepts. *Handbook of Multivariate Experimental Psychology*, 355–402.

Cervero, R. (2002). Built environments and mode choice: Toward a normative framework. *Transportation Research Part D: Transport and Environment*, *7*(4), 265–284. https://doi.org/10.1016/S1361-9209(01)00024-4

Cervero, R., & Duncan, M. (2003). Walking, bicycling, and urban landscapes: Evidence from the San Francisco Bay Area. *American Journal of Public Health*, *93*(9), 1478–1483.

Cervero, R., & Duncan, M. (2006). Which reduces vehicle travel more: Jobs-housing balance or retail-housing mixing? *Journal of the American Planning Association*, *72*(4), 475–490. https://doi.org/10.1080/01944360608976767

Cervero, R., Ferrell, C., & Murphy, S. (2002). Transit-oriented development and joint development in the united states: A literature review. *TCRP Research Results Digest*, (52), 144.

Cervero, R., & Gorham, R. (1995). Commuting in transit versus automobile neighborhoods. *Journal of the American Planning Association*, *61*(2), 210–225. https://doi.org/10.1080/01944369508975634

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D: Transport and*

Environment, *2*(3), 199–219. https://doi.org/10.1016/S1361-9209(97)00009-6

Cervero, R., & Murakami, J. (2010). Effects of built environments on vehicle miles traveled: Evidence from 370 U.S urbanized areas. *Environment and Planning A*, *42*(2), 400–418. https://doi.org/10.1068/a4236

Chadwick-Jones, J. K. (1976). *Social exchange theory: Its structure and influence in social psychology*. London, United Kingdom: Academic Press.

Chapin, F. S. (1955). Urban traffic: A function of land use [Review of the book Urban traffic: A function of land use, by R. B. Mitchell & C. Rapkin]. *Social Forces*, *33*(4), 402–403. https://doi.org/10.2307/2573023

Chatman, D. (2003). How density and mixed uses at the workplace affect personal commercial travel and commute mode choice. *Transportation Research Record: Journal of the Transportation Research Board*, *1831*, 193–201. https://doi.org/10.3141/1831-22

Chatman, D., & Klein, N. (2013). Why do immigrants drive less? Confirmations, complications, and new hypotheses from a qualitative study in new jersey, usa. *Transport Policy*, *30*, 336–344. https://doi.org/10.1016/j.tranpol.2013.10.002

Chen, C., Gong, H., & Paaswell, R. (2007). Role of the built environment on mode choice decisions: Additional evidence on the impact of density.

Transportation, *35*(3), 285–299. https://doi.org/10.1007/s11116-007-9153-5

Chen, J., & Li, S. (2017). Mode choice model for public transport with categorized latent variables. *Mathematical Problems in Engineering*. https://doi.org/10.1155/2017/7861945

Cheung, M. W. L. (2015). *Meta-analysis: A structural equation modeling approach*. Chichester, United Kingdom: John Wiley & Sons.

Christaller, W. (1966). *Central places in southern Germany*. Englewood Cliffs, NJ: Prentice Hall.

Cohen, J., & Cohen, P. (1983). *Applied multiple regression/correlation analysis for the behavioral sciences* (2nd ed.). Hillsdale, NJ: Lawrence Erlbaum Associates, Inc.

Committee on Physical Activity, Health, Transportation, and Land Use, Transportation. (2005). *Does the Built Environment Influence Physical Activity? Examining the Evidence* (TRB Special Report No. 282) (p. 248). Washington, D.C: Transportation Research Board, Institute of Medicine of the National Academies. Retrieved from http://onlinepubs.trb.org/onlinepubs/sr/sr282.pdf

Currie, J., & Walker, R. (2011). Traffic congestion and infant health: Evidence from E-ZPass. *American Economic Journal: Applied Economics*, *3*(1), 65–90. https://doi.org/10.1257/app.3.1.65

Danermark, B., Ekstrom, M., & Jakobsen, L. (2001). *Explaining society: An introduction to critical realism in the social sciences*. London, United Kingdom: Routledge.

Davis, A. F. (2004). *The impact of traffic congestion on household behavior: Three essays on the role of heterogeneity* (Doctoral dissertation). North Carolina State University, Raleigh, NC.

de Dios Ortúzar, J., & Willumsen, L. G. (2011). *Modelling transport* (4th Edition). Chichester, United Kingdom: John Wiley & Sons, Ltd.

De la Barra, T. (1989). *Integrated land use and transport modelling. Decision chains and hierarchies*. Cambridge, United Kingdom: Cambridge University Press.

Deakin, E. (1994). Urban transportation congestion pricing: Effects on urban form. In *Curbing gridlock: Peak-period fees to relieve traffic congestion - TRB Special report 242* (pp. 334–355). Washington, D.C.: The National Academies Press. Retrieved from http://trid.trb.org/view.aspx?id=390823

Diao, M., & Ferreira Jr, J. (2014). Vehicle miles traveled and the built environment: Evidence from vehicle safety inspection data. *Environment and Planning A*, *46*(12), 2991–3009. https://doi.org/10.1068/a140039p

Dillon, H. S. (2017). *Unraveling the effects of land use planning and energy policy on travel behavior* (Doctoral dissertation). University of California, Irvine.

Domencich, T. A., & McFadden, D. (1975). *Urban travel demand: A behavioral analysis*. Oxford, United Kingdom: North-Holland. Retrieved from https://trid.trb.org/view.aspx?id=48594

Downs, A. (1992). *Stuck in traffic*. Washington, DC: Brookings Institution Press.

Dubin, J. A., & McFadden, D. L. (1984). An econometric analysis of residential electric appliance holdings and consumption. *Econometrica*, *52*(2), 345–362. https://doi.org/10.2307/1911493

Dubin, R. (1991). Commuting patterns and firm decentralization. *Land Economics*, *67*(1), 15–29. https://doi.org/10.2307/3146482

Duncan, D. T., Aldstadt, J., Whalen, J., Melly, S. J., & Gortmaker, S. L. (2011). Validation of Walk Score® for estimating neighborhood walkability: An analysis of four U.S. metropolitan areas. *International Journal of Environmental Research and Public Health*, *8*(11), 4160–4179. https://doi.org/10.3390/ijerph8114160

Dunphy, R., & Fisher, K. (1996). Transportation, congestion, and density: New insights. *Transportation Research Record: Journal of the Transportation Research Board*, (1552), 89–96. https://doi.org/10.3141/1552-12

Echenique, M. H., Flowerdew, A. D. J., Hunt, J. D., Mayo, T. R., Skidmore, I. J., & Simmonds, D. C. (1988). The MEPLAN models of Bilbao, Dortmund and Leeds. *Transport Reviews*, *10*, 309–322. https://doi.org/10.1080/01441649008716764

Eliasson, J., & Mattsson, L.-G. (2000). A model for integrated analysis of household location and travel choices. *Transportation Research Part A: Policy and Practice*, *34*(5), 375–394. https://doi.org/10.1016/S0965-8564(99)00038-5

Ettema, D., & Nieuwenhuis, R. (2017). Residential self-selection and travel behaviour: What are the effects of attitudes, reasons for location choice and the built environment? *Journal of Transport Geography*, *59*, 146–155. https://doi.org/10.1016/j.jtrangeo.2017.01.009

Ewing, R. (2008). Characteristics, causes, and effects of sprawl: A literature review. In J. Marzluff, E. Shulenberger, W. Endlicher, M. Alberti, G. Bradley, C. Ryan, … C. ZumBrunnen (Eds.), *Urban Ecology: An International Perspective on the Interaction Between Humans and Nature* (pp. 519–535). New York, NY: Springer. https://doi.org/10.1007/978-0-387-73412-5_34

Ewing, R., & Cervero, R. (2001). Travel and the built environment: A synthesis. *Transportation Research Record: Journal of the Transportation Research Board*, (1780), 87–114. https://doi.org/10.3141/1780-10

Ewing, R., & Cervero, R. (2010a). Travel and the built environment: A meta-analysis. *Journal of the American Planning Association*, *76*(3), 265–294. https://doi.org/10.1080/01944361003766766

Ewing, R., & Cervero, R. (2010b). Travel and the built environment: a meta-analysis. *Journal of the American Planning Association*, *76*(3), 265–294.

Ewing, R., Hamidi, S., Gallivan, F., Nelson, A., & Grace, J. (2013). Combined effects of compact development, transportation investments, and road user pricing on vehicle miles traveled in urbanized areas. *Transportation Research Record: Journal of the Transportation Research Board*, *2397*, 117–124. https://doi.org/10.3141/2397-14

Ewing, R., Tian, G., & Lyons, T. (2018). Does compact development increase or reduce traffic congestion? *Cities*, *72*, 94–101. https://doi.org/10.1016/j.cities.2017.08.010

Fatmi, M. R., & Habib, M. A. (2017). Modelling mode switch associated with the change of residential location. *Travel Behaviour and Society, 9*, 21–28. https://doi.org/10.1016/j.tbs.2017.07.006

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention and behavior: An introduction to theory and research*. Boston, MA: Addison-Wesley.

Ganter, G., & Yeakel, M. (1980). *Human behavior and the social environment: A perspective for social work practice* (1st ed.). New York City, NY: Columbia University Press.

Giddens, A. (1979). Agency, Structure. In *Central Problems in Social Theory: Action, structure and contradiction in social analysis* (pp. 49–95).

London, United Kingdom: Macmillan Education UK. https://doi.org/10.1007/978-1-349-16161-4_3

Giddens, A. (1984). *The constitution of society: Outline of the theory of structuration*. Cambridge: PolitybPress.

Giuliano, G., & Narayan, D. (2003). Another look at travel patterns and urban form: The U.S. and Great Britain. *Urban Studies*, *40*(11), 2295–2312. https://doi.org/10.1080/0042098032000123303

Giuliano, G., & Small, K. A. (1993). Is the journey to work explained by urban structure? *Urban Studies*, *30*(9), 1485–1500. https://doi.org/10.1080/00420989320081461

Goldberger, A. S. (1964). *Econometric theory*. New York, NY: John Wiley & Sons.

Goldberger, A. S. (1972). Structural equation methods in the social sciences. *Econometrica: Journal of the Econometric Society*, *40*(6), 979–1001. https://doi.org/10.2307/1913851

Goldberger, A. S., & Duncan, O. D. (Eds.). (1973). *Structural equation models in the social sciences*. New York, NY: Seminar Press.

Golob, T. F., & Brownstone, D. (2005). *The impact of residential density on vehicle usage and energy consumption*. Irvine, CA: Institute of Transportation Studies University of California, Irvine.

Google LLC. (2018, July 19). Google maps platform terms of service. Retrieved from https://cloud.google.com/maps-platform/terms/

Gordon, P., Kumar, A., & Richardson, H. W. (1989). Congestion, changing metropolitan structure, and city size in the United States. *International Regional Science Review*, *12*(1), 45–56. https://doi.org/10.1177/016001768901200103

Gordon, P., Richardson, H. W., & Jun, M. J. (1991). The commuting paradox evidence from the top twenty. *Journal of the American Planning Association*, *57*(4), 416–420. https://doi.org/10.1080/01944369108975516

Greenwald, M., & Boarnet, M. (2001). Built environment as determinant of walking behavior: Analyzing nonwork pedestrian travel in Portland, Oregon. *Transportation Research Record: Journal of the Transportation Research Board*, *1780*, 33–41. https://doi.org/10.3141/1780-05

Hamilton, B. W., & Röell, A. (1982). Wasteful commuting. *Journal of Political Economy*, *90*(5), 1035–1053. https://doi.org/10.1086/261107

Handy, S. (1996). Understanding the link between urban form and nonwork travel behavior. *Journal of Planning Education and Research*, *15*(3), 183–198. https://doi.org/10.1177/0739456X9601500303

Handy, S. (2002). Travel behaviour--land use interactions: An overview and assessment of the research. In H. Mahmassani (Ed.), *Perpetual Motion:*

Travel Behavior Research Opportunities and Application Challenges (pp. 223–236). Bingley, UK: Emerald.

Handy, S. (2005). Smart growth and the transportation-land use connection: what does the research tell us? *International Regional Science Review*, *28*(2), 146–167.

Handy, S., Cao, X., & Mokhtarian, P. (2005). Correlation or causality between the built environment and travel behavior? Evidence from Northern California. *Transportation Research Part D: Transport and Environment*, *10*(6), 427–444. https://doi.org/10.1016/j.trd.2005.05.002

Handy, S., & Clifton, K. (2001). Local shopping as a strategy for reducing automobile travel. *Transportation*, *28*(4), 317–346. https://doi.org/10.1023/A:1011850618753

Handy, S., Lee, R., Maiss, R., Walters, J., & Parker, T. (2012). *Improved data and tools for integrated land use-transportation planning in California - Appendix A: Annotated literature review on land use-transportation relationships* (p. 35). Davis, CA: University of California, Davis.

Hanson, S. (1982). The determinants of daily travel-activity patterns: Relative location and sociodemographic factors. *Urban Geography*, *3*(3), 179–202. https://doi.org/10.2747/0272-3638.3.3.179

Hanson, S., & Giuliano, G. (Eds.). (2004). *The Geography of Urban Transportation* (3rd ed). New York: The Guilford Press.

Hanson, S., & Hanson, P. (1981). The travel-activity patterns of urban residents: Dimensions and relationships to sociodemographic characteristics. *Economic Geography*, *57*(4), 332–347. https://doi.org/10.2307/144213

Harvey, G. (1994). Transportation pricing and travel behavior. In *Curbing gridlock: Peak-period fees to relieve traffic congestion - TRB Special report 242* (pp. 89–114). Washington, D.C: The National Academies Press. Retrieved from https://trid.trb.org/view/390814

Hecht, A. (1974). The journey-to-work distance in relation to the socio-economic characteristics of workers. *Canadian Geographer / Le Géographe Canadien*, *18*(4), 367–378. https://doi.org/10.1111/j.1541-0064.1974.tb00210.x

Holtzclaw, J., Clear, R., Dittmar, H., Goldstein, D., & Haas, P. (2002). Location efficiency: Neighborhood and socio-economic characteristics determine auto ownership and use: Studies in Chicago, Los Angeles, and San Francisco. *Transportation Planning and Technology*, *25*(1), 1–27. https://doi.org/10.1080/03081060290032033

Horner, M. W. (2002). Extensions to the concept of excess commuting. *Environment and Planning A: Economy and Space*, *34*(3), 543–566. https://doi.org/10.1068/a34126

Horowitz, J. (1980). A utility maximizing model of the demand for multi-destination non-work travel. *Transportation Research Part B:*

Methodological, *14*(4), 369–386. https://doi.org/10.1016/0191-2615(80)90017-X

Hox, J. J., & Bechger, T. M. (2007). An introduction to structural equation modeling. *Family Science Review*, *11*, 354–373.

Hoyle, Rick H. (Ed.). (2012). *Handbook of structural equation modeling*. New York, NY: The Guilford Press.

Hsu, H. P. (2013). *Choices and constraints: Gender differences in travel behavior* (Doctoral dissertation). University of California, Irvine.

Huber, C. (2013). *Generalized Structural Equation Modeling Using Stata*. Presented at the Italian Stata Users Group Meeting.

Jöreskog, K. (1967). Some contributions to maximum likelihood factor analysis. *Psychometrika, 32*(4), 443–482. https://doi.org/10.1007/BF02289658

Jöreskog, K. (1969). A general approach to confirmatory maximum likelihood factor analysis. *Psychometrika*, *34*(2), 183–202. https://doi.org/10.1007/BF02289343

Jöreskog, K. (1970). A general method for estimating a linear structural equation system. *ETS Research Report Series*, *1970*(2), i–41. https://doi.org/10.1002/j.2333-8504.1970.tb00783.x

Jöreskog, K., & Goldberger, A. S. (1971). Factor analysis by generalized least squares. *ETS Research Report Series*, *1971*(1), 1–32. https://doi.org/10.1002/j.2333-8504.1971.tb00434.x

Jöreskog, K., & Lawley, D. (1968). New methods in maximum likelihood factor analysis. *ETS Research Bulletin Series*, *21*(1), 85–96. https://doi.org/10.1111/j.2044-8317.1968.tb00399.x

Jöreskog, K., & Sörbom, D. (1993). *LISREL 8: Structural equation modeling with the SIMPLIS command language*. Skokie, IL: Scientific Software International.

Kaplan, D. (2000). *Structural equation modeling: foundations and extensions*. Thousand Oaks, CA: Sage Publications.

Karash, K. H., Coogan, M. A., Adler, T., Cluett, C., Shaheen, S. A., Aizen, I., & Simon, M. (2008). *Understanding how individuals make travel and location decisions: Implications for public transportation* (TRB's Transit Cooperative Research Program (TCRP) - Report No. 123). Washington, D.C: Transportation Research Board.

Kim, J., & Brownstone, D. (2013). The impact of residential density on vehicle usage and fuel consumption: Evidence from national samples. *Energy Economics*, *40*, 196–206. https://doi.org/10.1016/j.eneco.2013.06.012

Kitamura, R., Mokhtarian, P. L., & Laidet, L. (1997). A micro-analysis of land use and travel in five neighborhoods in the San Francisco Bay Area. *Transportation*, *24*(2), 125–158. https://doi.org/10.1023/A:1017959825565

Kocher, J., & Lerner, M. (2018). Walk Score. Retrieved October 7, 2018, from https://www.walkscore.com/

Kockelman, K. (1997). Travel behavior as function of accessibility, land use mixing, and land use balance: Evidence from San Francisco Bay Area. *Transportation Research Record: Journal of the Transportation Research Board*, *1607*, 116–125. https://doi.org/10.3141/1607-16

Kockelman, K., Anjomani, A., Paul, B. M., Nostikasai, D., Tayyebi, A., & Kharel, G. (2010). *Design and application of accessible land-use modeling tools for Texas regions* (Technical Report No. 5-5667–01). Austin, TX: Center for Transportation Research, The University of Texas at Austin.

Koopmans, T. C. (1950). *Statistical inference in dynamic economic models*. New York, NY: John Wiley & Sons, Inc.

Koppelman, F. S., & Bhat, C. (2006). *A self instructing course in mode choice modeling: Multinomial and nested logit models*. Washington, DC: U.S. Department of Transportation. Retrieved from https://trid.trb.org/view/793000

Krasner, L. (1969). Behavior modification-values and training: The perspective of a psychologist. In *Behavior therapy: Appraisal and status* (pp. 537–566). New York, NY: McGraw-Hill.

Krishnamurthy, S., & Kockelman, K. (2003). Propagation of uncertainty in transportation land use models: Investigation of DRAM-EMPAL and UTPP predictions in Austin, Texas. *Transportation Research Record: Journal of the Transportation Research Board*, *1831*, 219–229. https://doi.org/10.3141/1831-25

Krizek, K. (2000). Pretest-posttest strategy for researching neighborhood-scale urban form and travel behavior. *Transportation Research Record: Journal of the Transportation Research Board*, *1722*, 48–55. https://doi.org/10.3141/1722-06

Kuppam, A., Pendyala, R., & Rahman, S. (1999). Analysis of the role of traveler attitudes and perceptions in explaining mode-choice behavior. *Transportation Research Record: Journal of the Transportation Research Board*, *1676*, 68–76. https://doi.org/10.3141/1676-09

Kuzmyak, J. R. (2012). *Land use and traffic congestion* (Technical Report No. FHWA-AZ-12-618) (p. 278). Phoenix, Arizona: Arizona Department of Transportation Research Center.

Lawley, D. N., & Maxwell, A. E. (1962). Factor analysis as statistical method. *Journal of the Royal Statistical Society*, *12*(3), 209–229. https://doi.org/10.2307/2986915

Lei, P. W., & Wu, Q. (2007). Introduction to structural equation modeling: Issues and practical considerations. *Educational Measurement: Issues and Practice*, *26*(3), 33–43. https://doi.org/10.1111/j.1745-3992.2007.00099.x

Lemp, J. D., Kockelman, K., & Damien, P. (2010). The continuous cross-nested logit model: Formulation and application for departure time choice. *Transportation Research Part B: Methodological*, *44*(5), 646–661. https://doi.org/10.1016/j.trb.2010.03.001

Lerman, S. R. (1976). Location, housing, automobile ownership, and mode to work: A joint choice model. *Transportation Research Record*, (610). Retrieved from https://trid.trb.org/view/53665

Levine, J. (1998). Rethinking accessibility and jobs-housing balance. *Journal of the American Planning Association*, *64*(2), 133–149. https://doi.org/10.1080/01944369808975972

Levy, J. I., Buonocore, J. J., & Von Stackelberg, K. (2010). Evaluation of the public health impacts of traffic congestion: A health risk assessment. *Environmental Health*, *9*, 65. https://doi.org/10.1186/1476-069X-9-65

Lin, J. J., & Yang, A.-T. (2009). Structural analysis of how urban form impacts travel demand: Evidence from Taipei. *Urban Studies*, *46*(9), 1951–1967. https://doi.org/10.1177/0042098009106017

Lin, T., Wang, D., & Guan, X. (2017). The built environment, travel attitude, and travel behavior: Residential self-selection or residential determination?

Journal of Transport Geography, *65*, 111–122. https://doi.org/10.1016/j.jtrangeo.2017.10.004

Linn, J., Wang, Z., & Xie, L. (2016). Who will be affected by a congestion pricing scheme in Beijing? *Transport Policy*, *47*, 34–40. https://doi.org/10.1016/j.tranpol.2015.12.006

Litman, T. (2014). Congestion evaluation best practices. In *International Transportation Economic Development Conference*. Dallas, TX.

Litman, T., & Colman, S. B. (2001). Generated traffic: Implications for transport planning. *Institute of Transportation Engineers. ITE Journal*, *71*(4), 38–47.

Liu, C., & Shen, Q. (2011). An empirical analysis of the influence of urban form on household travel and energy consumption. *Computers, Environment and Urban Systems*, *35*(5), 347–357. https://doi.org/10.1016/j.compenvurbsys.2011.05.006

Lo, A. W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *Journal of Portfolio Management*, *30*(5). http://dx.doi.org/10.3905/jpm.2004.442611

Lo, A. W. (2017). *Adaptive markets: Financial evolution at the speed of thought*. Princeton, NJ: Princeton University Press.

Lomax, T. J., & Schrank, D. L. (2002). *Using travel time measures to estimate mobility and reliability in urban areas* (Technical Report No. FHWA/TX-02/1511-3). College Station, TX: Texas A&M Transportation Institute.

Lomax, T. J., Turner, S., & Shunk, G. (1997). *Quantifying congestion—Final report and user's guide* (NCHRP Report No. 398). Washington, D.C: National Cooperative Highway Research Program, National Research Council. Retrieved from https://trid.trb.org/view.aspx?id=475257

Lowry, I. S. (1964). *A model of metropolis*. Santa Monica, CA: Rand Corporation.

Lucas, R. E., & Rossi–Hansberg, E. (2002). On the internal structure of cities. *Econometrica*, *70*(4), 1445–1476. https://doi.org/10.1111/1468-0262.00338

Mackie, J. L. (1965). Causes and conditions. *American Philosophical Quarterly*, *2*(4), 245–264.

Maddison, D. (1997). The true cost of road transport in the United Kingdom. In O. Hohmeyer, K. Rennings, & R. L. Ottinger (Eds.), *Social Costs and Sustainability* (pp. 357–379). Berlin, Germany: Springer. https://doi.org/10.1007/978-3-642-60365-5_22

Manaugh, K., Miranda-Moreno, L. F., & El-Geneidy, A. M. (2010). The effect of neighbourhood characteristics, accessibility, home–work location, and demographics on commuting distances. *Transportation*, *37*(4), 627–646. https://doi.org/10.1007/s11116-010-9275-z

Martínez, F. J. (1996). MUSSA: Land use model for Santiago city. *Transportation Research Record: Journal of the Transportation Research Board*, (1552), 126–134. https://doi.org/10.3141/1552-18

Maslow, A. H. (1943). The authoritarian character structure. *The Journal of Social Psychology*, *18*(2), 401–411. https://doi.org/10.1080/00224545.1943.9918794

Mauch, M., & Taylor, B. (1997). Gender, race, and travel behavior: Analysis of household-serving travel and commuting in San Francisco Bay Area. *Transportation Research Record: Journal of the Transportation Research Board*, *1607*, 147–153. https://doi.org/10.3141/1607-20

McCormack, G. R., Giles-Corti, B., & Bulsara, M. (2008). The relationship between destination proximity, destination mix and physical activity behaviors. *Preventive Medicine*, *46*(1), 33–40. https://doi.org/10.1016/j.ypmed.2007.01.013

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, *3*(4), 303–328. https://doi.org/10.1016/0047-2727(74)90003-6

Mead, G. H. (1934). *Mind, self and society* (Vol. 111). Chicago, IL: Chicago University of Chicago Press.

Melo, R. A., Rodriguez, D., & Zarruk, D. (2018). Distance and travel time between two points from google maps (Version 3.4) [R Package "gmapsdistance"]. Retrieved from https://cran.r-project.org

Mitchell, R. B., & Rapkin, C. (1954). *Urban traffic: A function of land use*. New York, NY: Columbia University Press.

Mouzelis, N. P. (2008). *Modern and postmodern social theorizing: Bridging the divide*. Cambridge, United Kingdom: Cambridge University Press.

Muro-Rodríguez, A. I., Perez-Jiménez, I. R., & Gutiérrez-Broncano, S. (2017). Consumer behavior in the choice of mode of transport: A case study in the toledo-madrid corridor. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.01011

Muthén, B. (1984). A general structural equation model with dichotomous, ordered categorical, and continuous latent variable indicators. *Psychometrika*, *49*(1), 115–132. https://doi.org/10.1007/BF02294210

Muthén, L., & Muthén, B. (2012). *Mplus user's guide* (7th ed.). Los Angeles, CA: Muthén & Muthén.

Næss, P. (2006). *Urban structure matters: Residential location, car dependence and travel behaviour* (1st ed.). London, United Kingdom: Routledge.

Newman, P., & Kenworthy, J. (1989). *Cities and automobile dependence: An international sourcebook*. Aldershot, England: Gower Publishing.

Newman, P., & Kenworthy, J. (1996). The land use—transport connection: An overview. *Land Use Policy*, *13*(1), 1–22. https://doi.org/10.1016/0264-8377(95)00027-5

Oppenheim, N. (1995). *Urban travel demand modeling: From individual choices to general equilibrium*. New York, NY: Wiley.

Pallant, J. (2013). *Spss survival manual: A step by step guide to data analysis using IBM SPSS* (5th ed.). Maidenhead, England: Open University Press.

Pampel, F. C. (2000). *Logistic regression: A primer*. Thousand Oaks, CA: Sage Publications.

Parsons, T. (1977). *The evolution of societies*. Saddle River, NJ: Prentice Hall.

Peng, Z., Dueker, K., & Strathman, J. (1996). Residential location, employment location, and commuter responses to parking charges. *Transportation Research Record: Journal of the Transportation Research Board*, *1556*, 109–118. https://doi.org/10.3141/1556-13

Polzin, S. E. (2006). *The case for moderate growth in vehicle miles of travel: A critical juncture in US travel behavior trends* (p. 39). Tampa, FL: Center for Urban Transportation Research, University of South Florida.

Pratt, R. H. (2013). *Traveler response to transportation system changes handbook* (3rd ed.). Washington, D.C: Transportation Research Board. Retrieved from https://trid.trb.org/view.aspx?id=1243652

Putman, S. H. (1983). *Integrated urban models: Policy analysis of transportation and land use* (1st ed.). Abingdon, England: Routledge.

Rabe-Hesketh, S., Skrondal, A., & Pickles, A. (2004). Generalized multilevel structural equation modeling. *Psychometrika*, *69*(2), 167–190. https://doi.org/10.1007/BF02295939

Rasouli, S., & Timmermans, H. (2014). Activity-based models of travel demand: Promises, progress and prospects. *International Journal of Urban Sciences*, *18*(1), 31–60. https://doi.org/10.1080/12265934.2013.835118

Rasouli, S., & Timmermans, H. (Eds.). (2015). *Bounded rational choice behaviour: Applications in transport* (1st ed.). Bingley, UK: Emerald Publishing.

Resource Systems Group (RSG). (2015). *Report: 2015 household travel survey*. Seattle, WA: Puget Sound Regional Council (PSRC). Retrieved from https://www.psrc.org/household-travel-survey-program

Rogers, C. R. (1959). A theory of therapy, personality, and interpersonal relationships, as developed in the client-centered framework. In S. Koch (Ed.), *Psychology; a study of a science: Formulations of the person and the social context* (Vol. 3). New York, NY, US: McGraw-Hill.

Rose, J. M., & Martínez, F. J. (2007). Towards a land-use and transport interaction framework. In D. A. Hensher & K. J. Button (Eds.), *Handbook* *of Transport Modelling* (2nd ed., Vol. 1, pp. 181–201). Bingley, UK: Emerald Group. https://doi.org/10.1108/9780857245670-009

Ross, C. L., & Dunning, A. E. (1997). *Land use transportation interaction: An examination of the 1995 NPTS data*. Atlanta, GA: Georgia Institute of Technology. Retrieved from https://doi.org/10.21949/1404566

Saka, A. A. (2009). *Statewide GIS mapping of recurring congestion corridors* (Technical report No. SHA-AX416A21). Baltimore, MD: Department of Transportation and Urban Infrastructure Studies School of Engineering Morgan State University. Retrieved from https://trid.trb.org/view/901472

Sánchez, M. I. O., & González, E. M. (2016). Gender differences in commuting behavior: Women's greater sensitivity. *Transportation Research Procedia*, *18*, 66–72. https://doi.org/10.1016/j.trpro.2016.12.009

Sangkapichai, M., & Saphores, J. D. (2009). Why are Californians interested in hybrid cars? *Journal of Environmental Planning and Management*, *52*(1), 79–96. https://doi.org/10.1080/09640560802504670

Sardari, R., Hamidi, S., & Pouladi, R. (2018). Effects of traffic congestion on vehicle miles traveled. *Transportation Research Record*. https://doi.org/10.1177/0361198118791865

Sarzynski, A., Wolman, H. L., Galster, G., & Hanson, R. (2006). Testing the conventional wisdom about land use and traffic congestion: The more we sprawl, the less we move? *Urban Studies*, *43*(3), 601–626. https://doi.org/10.1080/00420980500452441

Sayer, A. (1992). *Method in social science. A realist approach* (2nd ed.). London, United Kingdom: Routledge.

Schönfelder, S., & Axhausen, K. W. (2010). *Urban rhythms and travel behaviour: Spatial and temporal phenomena of daily travel*. London, United Kingdom: Routledge.

Schrank, D. L., Eisele, W. L., & Lomax, T. J. (2005). *The keys to estimating mobility in urban areas, applying definitions and measures that everyone understands, Second edition* (White Paper). College Station, TX: Texas Transportation Institute, The Texas A&M University System. Retrieved from https://static.tti.tamu.edu/tti.tamu.edu/documents/TTI-2005-2.pdf

Schwanen, T., Dieleman, F., & Dijst, M. (2004). The impact of metropolitan structure on commute behavior in the Netherlands: A multilevel approach. *Growth and Change*, *35*(3), 304–333. https://doi.org/10.1111/j.1468-2257.2004.00251.x

Schwanen, T., Dijst, M., & Dieleman, F. M. (2001). Empirical analysis of the relationship between urban form and travel time (pp. 233–253). Presented at the 28th Colloquium Vervoersplanologisch Speurwerk (CVS), Delft, Netherlands: Colloquium Vervoersplanologisch Speurwerk. Retrieved from https://trid.trb.org/view/645568

Schwanen, T., & Mokhtarian, P. (2005). What affects commute mode choice: Neighborhood physical structure or preferences toward neighborhoods? *Journal of Transport Geography*, *13*(1), 83–99. https://doi.org/10.1016/j.jtrangeo.2004.11.001

Simon, H. A. (1982). *Models of Bounded Rationality: Empirically grounded economic reason*. Cambridge, MA: MIT Press.

Small, K. A., & Song, S. (1992). “Wasteful” commuting: A resolution. *Journal of Political Economy*, *100*(4), 888–898. https://doi.org/10.1086/261844

Small, K. A., & Winston, C. (1999). The demand for transportation: Models and applications. In J. A. Gómez-Ibáñez, W. B. Tye, & C. Winston (Eds.), *Essays in transportation economics and policy : a handbook in honor of John R. Meyer*. Retrieved from https://trid.trb.org/view/500076

Soltani, A. (2017). Social and urban form determinants of vehicle ownership: Evidence from a developing country. *Transportation Research Part A: Policy and Practice*, *96*, 90–100. https://doi.org/10.1016/j.tra.2016.12.010

Srinivasan, S., & Ferreira, J. (2002). Travel behavior at the household level: Understanding linkages with residential choice. *Transportation Research Part D: Transport and Environment*, *7*(3), 225–242. https://doi.org/10.1016/S1361-9209(01)00021-9

StataCorp. (2017). *Stata Structural Equation Modeling* (Reference Manual No. 13) (p. 583). College Station, TX: Stata Press Publication.

Stern, E., Salomon, I., & Bovy, P. H. (Eds.). (2002). *Travel behaviour: Spatial patterns, congestion and modelling*. Cheltenham, United Kingdom: Edward Elgar Publishing.

Stopher, P. R., Meyburg, A. H., & Brög, W. (Eds.). (1981). *New horizons in travel-behavior research*. Lexington, MA: Lexington Books.

Suel, E., & Polak, J. W. (2017). Development of joint models for channel, store, and travel mode choice: Grocery shopping in London. *Transportation Research Part A: Policy and Practice*, *99*, 147–162. https://doi.org/10.1016/j.tra.2017.03.009

Sweet, M. N., & Chen, M. (2011). Does regional travel time unreliability influence mode choice? *Transportation*, *38*(4), 625–642. https://doi.org/10.1007/s11116-011-9335-z

Tal, G., & Handy, S. (2010). Travel behavior of immigrants: An analysis of the 2001 National Household Transportation Survey. *Transport Policy*, *17*(2), 85–93. https://doi.org/10.1016/j.tranpol.2009.11.003

Thaler, R. H. (2017). Behavioral economics. *Journal of Political Economy*, *125*(6), 1799–1805. https://doi.org/10.1086/694640

Tilahun, N., & Fan, Y. (2014). Transit and job accessibility: An empirical study of access to competitive clusters and regional growth strategies for enhancing transit accessibility. *Transport Policy*, *33*, 17–25. https://doi.org/10.1016/j.tranpol.2014.02.002

Tilley, S., & Houston, D. (2016). The gender turnaround: Young women now travelling more than young men. *Journal of Transport Geography*, *54*, 349–358. https://doi.org/10.1016/j.jtrangeo.2016.06.022

Train, K. (1986). *Qualitative choice analysis: Theory, econometrics, and an application to automobile demand*. (M. L. Manheim, Ed.). Cambridge, MA: MIT Press.

Tran, M. T., Zhang, J., Chikaraishi, M., & Fujiwara, A. (2016). A joint analysis of residential location, work location and commuting mode choices in Hanoi, Vietnam. *Journal of Transport Geography*, *54*, 181–193. https://doi.org/10.1016/j.jtrangeo.2016.06.003

Transportation Research Board. (2009). *Driving and the built environment: The effects of compact development on motorized travel, energy use, and CO2 emissions* (TRB Special Report No. 298). Washington, D.C.: Transportation Research Board.

Trowbridge, M. J., & McDonald, N. C. (2008). Urban sprawl and miles driven daily by teenagers in the United States. *American Journal of Preventive Medicine*, *34*(3), 202–206. https://doi.org/10.1016/j.amepre.2007.11.013

Turner, S., Lomax, T., & Levinson, H. (1996). Measuring and estimating congestion using travel time-based procedures. *Transportation Research Record: Journal of the Transportation Research Board*, *1564*, 11–19. https://doi.org/10.3141/1564-02

U. S. General Accounting Office. (1989). *Traffic congestion: Trends, measures, and effects* (Report No. PEMD-90-1). Washington, D.C: U.S General Accounting Office. Retrieved from http://www.gao.gov/products/PEMD-90-1

U.S. Department of Transportation Federal Highway Administration. (2014). *Reducing vehicle miles traveled - Statutory language*. Federal Highway Administration.

U.S Department of Transportation, Federal Highway Administration. (2015). *Status of the nation's highways, bridges, and transit: Conditions and performance*. Washington, D.C: U.S Department of Transportation. Retrieved from https://www.fhwa.dot.gov/policy/2015cpr/pdfs/2015cpr.pdf

U.S. Geological Survey, Gap Analysis Program (GAP). (2016). Protected Areas Database of the United States (PAD-US), Version 1.4 Combined Feature Class. U.S. Geological Survey. Retrieved from https://gapanalysis.usgs.gov/padus/

U.S. Senate, Subcommittee on Transportation and Related Agencies. (1990). *Effects of congestion on mobility in New Jersey*. Washington, D.C: U.S Government Printing Office.

Van Acker, V., Mokhtarian, P. L., & Witlox, F. (2014). Car availability explained by the structural relationships between lifestyles, residential location, and underlying residential and travel attitudes. *Transport Policy*, *35*, 88–99. https://doi.org/10.1016/j.tranpol.2014.05.006

Van Acker, V., & Witlox, F. (2007). Explaining travel behavior: Towards a new conceptual framework and modeling technique. Presented at the 11th World Conference on Transport Research World Conference on Transport Research Society (WCTRS), Berkeley, CA.

Van Acker, V., Witlox, F., & Wee, B. V. (2007). The effects of the land use system on travel behavior: A structural equation modeling approach. *Transportation Planning and Technology*, *30*(4), 331–353. https://doi.org/10.1080/03081060701461675

Van Wee, B. (2009). Self-selection: A key to a better understanding of location choices, travel behaviour and transport externalities? *Transport Reviews*, *29*(3), 279–292. https://doi.org/10.1080/01441640902752961

Von Thunen, J. (1826). *The isolated state*. London, United Kingdom: Pergamon.

Waddell, P. (1993). Exogenous workplace choice in residential location models: is the assumption valid? *Geographical Analysis*, *25*(1), 65–82. https://doi.org/10.1111/j.1538-4632.1993.tb00280.x

Walker, J., & Ben-Akiva, M. (2002). Generalized random utility model. *Mathematical Social Sciences*, *43*(3), 303–343. https://doi.org/10.1016/S0165-4896(02)00023-9

Walters, J., Breiland, C., Jimenez, G., & Lee, R. (2012). *Improved data and tools for integrated land use-transportation planning in California*. Davis, CA: University of California, Davis. Retrieved from http://trid.trb.org/view.aspx?id=1309278

Wegener, M. (2004). Overview of land use transport models. In D. A. Hensher, K. J. Button, K. E. Haynes, & P. R. Stopher (Eds.), *Handbook of transport geography and spatial systems* (Vol. 5, pp. 127–146). Bingley, UK: Emerald Group Publishing.

Whalen, J. (2015). Walk score and transit score API: R package 'walkscoreAPI' (Version 1.2). Retrieved from https://cran.r-project.org

White, M. J. (1986). Sex differences in urban commuting patterns. *The American Economic Review*, *76*(2), 368–372.

White, M. J. (1988). Urban commuting journeys are not "wasteful." *Journal of Political Economy*, *96*(5), 1097–1110. https://doi.org/10.1086/261579

Wright, S. (1921). Correlation and causation. *Journal of Agricultural Research*, *20*(7), 557–585.

Xu, R. (2011). *Dynamic discrete choice models for car ownership modeling* (Doctoral dissertation). University of Maryland, College Park, College Park, MD.

Yang, L., Zheng, G., & Zhu, X. (2013). Cross-nested logit model for the joint choice of residential location, travel mode, and departure time. *Habitat*

International, *38*, 157–166. https://doi.org/10.1016/j.habitatint.2012.06.002

Zaman, H. (2010). *Investigation of commuting mode choice with respect to TDM policies* (Master's thesis). University of Alberta, Edmonton, Canada.

Zax, J. S. (1990). Race and commutes. *Journal of Urban Economics*, *28*(3), 336–348. https://doi.org/10.1016/0094-1190(90)90032-I

Zhang, J., & Van Acker, V. (2017). Life-oriented travel behavior research: An overview. *Transportation Research Part A: Policy and Practice*, *104*, 167–178. https://doi.org/10.1016/j.tra.2017.06.004

Zhang, M. (2004). The role of land use in travel mode choice: Evidence from Boston and Hong Kong. *Journal of the American Planning Association*, *70*(3), 344–360. https://doi.org/10.1080/01944360408976383

Zhang, W., & Kockelman, K. (2016). Congestion pricing effects on firm and household location choices in monocentric and polycentric cities. *Regional Science and Urban Economics*, *58*, 1–12. https://doi.org/10.1016/j.regsciurbeco.2016.01.002

Zhang, Z., Jin, W., Jiang, H., Xie, Q., Shen, W., & Han, W. (2017). Modeling heterogeneous vehicle ownership in China: A case study based on the Chinese national survey. *Transport Policy*, *54*, 11–20. https://doi.org/10.1016/j.tranpol.2016.10.005

Biographical Information

Reza Sardari was born in Tehran, Iran. After earning his bachelor’s degree in Urban Studies at Yazd University in 2004, Reza entered Tarbiat Modares University and earned his master's degree in Urban & Regional Planning in 2007. During the next 4 years, he was employed as a GIS instructor at Qazvin International University and also involved in World Bank and UN-Habitat projects. He began doctoral studies in Urban Planning and Public Policy at the University of Texas at Arlington (UTA) in 2012. During his Ph.D. studies at UTA, Reza worked as a graduate research assistant at the Institute of Urban Studies, where he contributed technical assistance for multiple GIS-based projects. In 2013, Reza worked as a GIS\Planner intern at the City of Farmers Branch and served as the President of the Student Planning Association. Reza received his GISP license in 2014 and started working as a GIS analyst and transportation planner at C&M Associates, Inc., where he is involved in various traffic and revenue studies.

Reza has been awarded several scholarships including ACSP 2017, the Dr. Ben-Akiva 2015 MIT award, the AirSage PASS 2015 award, the North Central Texas American Planning Association (NCTAPA) 2014 award, the ESRI Geodesign Summit 2014 scholarship, the APA Midwest Section Texas 2013 award, and the SIAWE 2012 Scholarship. The following publications were a result of his work conducted during doctoral study:

- Effects of Traffic Congestion on Vehicle Miles Traveled. Transportation Research Record, 2018.
- Using Census Data and Lorenz Curves to Measure Public Transportation Equity Within the DART Service Area, CTPP Status Report No. FHWA-HEP-18-046, 2018.
- Using Census Data and Lorenz Curves to Measure Public Transportation Equity Within the DART Service Area. Presented at the TRB Conference, Applying Census Data for Transportation, Kansas City, MO, 2017.