Analysis of Activity-Travel Patterns and Tour Formation of Transit Users

April 2021

A research report from the Pacific Southwest Region University Transportation Center

Michael G. McNally, University of California Irvine

Rezwana Rafiq, University of California Irvine

Pacific Southwest Region UTC
University Transportation Center

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. PSR-19-33	**2. Government Accession No.** N/A	**3. Recipient's Catalog No.** N/A
4. Title and Subtitle Analysis of Activity-Travel Patterns and Tour Formation of Transit Users		**5. Report Date** April 30, 2021 **6. Performing Organization Code** N/A
7. Author(s) Michael G. McNally, 0000-0003-2799-5389 Rezwana Rafiq, 0000-0002-7177-5415		**8. Performing Organization Report No.** PSR-19-33
9. Performing Organization Name and Address METRANS Transportation Center University of Southern California University Park Campus, RGL 216 Los Angeles, CA 90089-0626		**10. Work Unit No.** N/A **11. Contract or Grant No.** USDOT Grant 69A3551747109; TO-033
12. Sponsoring Agency Name and Address U.S. Department of Transportation Office of the Assistant Secretary for Research and Technology 1200 New Jersey Avenue, SE, Washington, DC 20590		**13. Type of Report and Period Covered** Final report (05/01/2020 – 04/30/2021) **14. Sponsoring Agency Code** USDOT OST-R

15. Supplementary Notes
Project webpage: https://www.metrans.org/research/analysis-of-activity-travel-patterns-and-tour-formation-of-transit-users

16. Abstract
This study analyzed the complex travel behavior of transit users by expanding conventional trip-based approaches by considering full activity-travel *tours* and *patterns* as basic units of analysis. A tour was defined as a sequence of trips that begins and ends at home and a pattern was defined as an entire day's sequence of activities and associated travel. We considered basic descriptive analyses to first analyze work tours—the tours that contain at least one work activity—of transit commuters and then used Structural Equation Modeling to identify the factors that determine the work tour choices. Latent Class Analysis (LCA) was then used to describe the pattern behaviors of all transit users. The results obtained using the 2017 National Household Travel Survey dataset suggested that 80 percent of work tours consisted of seven dominant tours and that work tour choice was influenced by a set of socio-demographics, built environment, and activity-travel characteristics. The LCA model suggested that transit users can be divided into five distinct classes, namely regular 9-to-5 commuters, after-work stop commuters, multimodal multiple trip makers, morning non-work travelers, and recurrent transit users, where each class had a representative activity-travel pattern. The results can help transit agencies to identify transit user groups with particular activity patterns and to consider market strategies to address user travel needs and to improve the quality of services provided.

17. Key Words Transit, travel behavior, commuters, travel patterns		**18. Distribution Statement** No restrictions.	
19. Security Classif. (of this report) Unclassified	**20. Security Classif. (of this page)** Unclassified	**21. No. of Pages** 86	**22. Price** N/A

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

TABLE OF CONTENTS

About the Pacific Southwest Region University Transportation Center

The Pacific Southwest Region University Transportation Center (UTC) is the Region 9 University Transportation Center funded under the US Department of Transportation's University Transportation Centers Program. Established in 2016, the Pacific Southwest Region UTC (PSR) is led by the University of Southern California and includes seven partners: Long Beach State University; University of California, Davis; University of California, Irvine; University of California, Los Angeles; University of Hawaii; Northern Arizona University; Pima Community College.

The Pacific Southwest Region UTC conducts an integrated, multidisciplinary program of research, education and technology transfer aimed at *improving the mobility of people and goods throughout the region.* Our program is organized around four themes: 1) technology to address transportation problems and improve mobility; 2) improving mobility for vulnerable populations; 3) Improving resilience and protecting the environment; and 4) managing mobility in high growth areas.

U.S. Department of Transportation (USDOT) Disclaimer

California Department of Transportation (CALTRANS) Disclaimer

Disclosure

The Principal Investigator Professor Michael G. McNally, and Research Scientist Dr. Rezwana Rafiq conducted this research titled, "Analysis of Activity-travel Patterns and Tour Formation of Transit Users" at the Institute of Transportation Studies in the University of California, Irvine. The research took place from 05/01/2020 to 04/30/2021 and was funded by a grant TO-033 from the California Department of Transportation in the amount of $80,608.68. The research was conducted as part of the Pacific Southwest Region University Transportation Center research program.

Acknowledgments

The authors would like to acknowledge the USDOT Pacific Southwest Region University Transportation Center and the California Department of Transportation (Caltrans) for providing funding for this research. They would like to thank Nathan Loebs, Caltrans task order manager for serving as the project mentor and providing useful feedback. The authors also thank the Institute of Transportation Studies (ITS) at the University of California, Irvine for providing administrative support. Research results under this project have been presented at the 100th Transportation Research Board Annual Meeting in 2021 (presentation numbers TRBAM-21-03193 and TRBAM-21-03013).

Abstract

This study analyzed the complex travel behavior of transit users by expanding conventional trip-based approaches by considering full activity-travel *tours* and *patterns* as basic units of analysis. A tour was defined as a sequence of trips that begins and ends at home and a pattern was defined as an entire day's sequence of activities and associated travel. We considered basic descriptive analyses to first analyze work tours—the tours that contain at least one work activity—of transit commuters and then used Structural Equation Modeling to identify the factors that determine the work tour choices. Latent Class Analysis (LCA) was then used to describe the pattern behaviors of all transit users. The results obtained using the 2017 National Household Travel Survey dataset suggested that 80 percent of work tours consisted of seven dominant tours and that work tour choice was influenced by a set of socio-demographics, built environment, and activity-travel characteristics. The LCA model suggested that transit users can be divided into five distinct classes, namely regular 9-to-5 commuters, after-work stop commuters, multimodal multiple trip makers, morning non-work travelers, and recurrent transit users, where each class had a representative activity-travel pattern. The results can help transit agencies to identify transit user groups with particular activity patterns and to consider market strategies to address user travel needs and to improve the quality of services provided.

Analysis of Activity-Travel Patterns and Tour Formation of Transit Users

Executive Summary

The complexity of travel behavior has evolves over time as travelers respond to various activity demands and the changing supply environment, measured by congestion, cost, and emerging technologies. Complexity in travel behavior is often manifested by an increasing tendency to chain several activity purposes within a tour to minimize total travel time and the number of trips. In response, travelers seek more flexible travel modes to complete their complex travel demand. While personal vehicles arguably provide the most flexibility in terms of managing travel needs, a more sustainable mode of transport is public transit. However, public transit often offers less flexibility and mobility services than a private car in chaining activities due to temporal and spatial constraints such as fixed routes and schedules, transfer requirements, waiting times, and access/egress issues. Its widespread adoption is arguably dependent on its ability to offer effective chaining of activities as well as trips. Unfortunately, little is known in the context of American travel about the complex travel behavior of transit users. Our goal was to address this research gap. In this study, we explored the *tour* formation and overall activity-travel *patterns* of transit users. Here, a tour was defined as a sequence of trips that begins and ends at home and contains at least one out-of-home activity. A pattern was defined as the complete sequence of activities and trips made over a full 24-hour day.

The first objective of this research is to analyze *how* and *when* public transit commuters incorporate non-work activities within their work tours, constrained by factors such as work time commitments, transit operating characteristics, and access/egress issues. In particular, we identified dominant patterns of work tours made by transit commuters and analyze these tours using a set of activity-travel analytics and data from the 2017 National Household Travel Survey (NHTS). The primary insights were: (1) about 80 percent of work tours consist of seven dominant patterns whereas the remaining 20 percent of tours demonstrate a total of 106 diverse and more complicated patterns; (2) half of the transit work tours are complex; (3) most simple tours are transit-only tours whereas most complex tours are multi-modal tours; and (4) transit use is more complex than the traditional home to work commute with a diverse set of choices at various stages of activity scheduling. These study findings are discussed in Chapter 2.

The second objective was to analyze the activity pattern behavior of transit users by using a comprehensive approach—Latent Class Analysis (LCA). In particular, we identified latent classes of transit users based on heterogeneity in activity-travel patterns and then associated those classes with socio-demographic characteristics of transit users in the class. Based on the 2017 NHTS data, the LCA model suggested that the transit users can be divided into five distinct classes where each class had a representative activity-travel pattern. Class 1 constituted primarily employed white males who make transit-dominant simple work tours. Class 2 was primarily composed of white females who make complex work tours. Employed millennials comprised Class 3 and made multimodal complex tours. Class 4 represented younger non-white

and older adult groups who made transit-dominant simple non-work tours. Last, Class 5 members made complex non-work tours with recurrent transit use and primarily comprised single older women. In addition, we observed the activity-travel patterns of four disadvantaged groups of transit users, namely people who lived in (1) carless households, (2) low-income households, (3) rural areas, and (4) who were older adults. We found that these disadvantaged groups used transit differently than non-disadvantaged groups. More specifically, these groups of people typically used transit in non-work activity-travel patterns. Detailed discussion is provided in Chapter 3.

Finally, we developed a tour choice model to characterize public transit commuters (*who*) based on the complexity of work tours and also to assess the impacts of demographic, location, and activity-travel factors on the likelihood of a transit commuter choosing a particular type of work tour (*why*). Based on 2017 NHTS data, a Structural Equation Model (SEM) was developed. The results suggested that married men with no children and high vehicle ownership living in low-density areas tended to make simple work tours while single, non-millennial women with children who live in high-density neighborhoods were more likely to make complex work tours. Also, millennial white males with higher income and higher education who are living in denser areas were more likely to make complex tours with work-based sub-tours. Moreover, denser residential neighborhoods, flexible work schedules, and private vehicle availability in work tours were observed to increase the propensity of making any kind of complex tours. Chapter 4 presents these research outcomes.

Transit agencies can benefit from the research findings on tour formation and daily activity-travel patterns of transit users by developing market strategies to address transit users travel needs and thus to improve the quality of transit serviced provided.

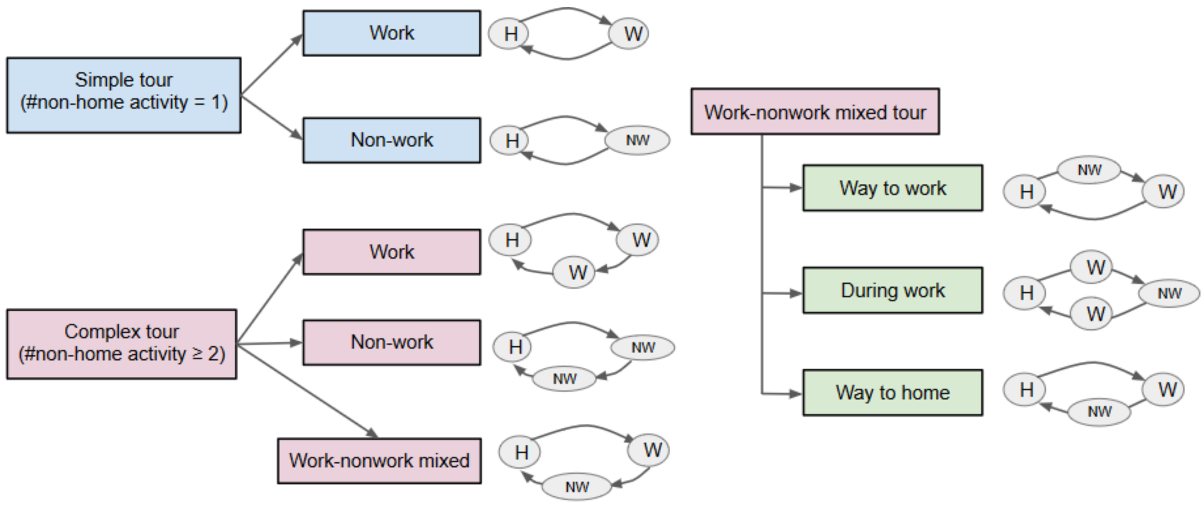
Introduction

Public transit is considered a sustainable mode of transportation that can reduce automobile dependency and thus can mitigate some of the negative consequences of automobile use, including congestion, air pollution, and energy consumption (Federal Highway Administration, 2018). However, with operations typically based on fixed routes and fixed schedules, public transit offers lower flexibility and mobility services than automobiles, particularly in satisfying complex travel needs (Hensher and Reyes, 2000) and thus is considered a less attractive mode to many potential users. A better understanding of daily activity-travel patterns of transit users is needed to allow transit operators to evaluate their services and to implement strategies to attract more people to transit.

In recent years, a wealth of research has been completed that focused on techniques to extract information on transit user's daily activity-travel patterns by mining transit smart card data (Ma *et al.*, 2013; Ma *et al.*, 2017; Bhaskar and Chung, 2014; Morency *et al.*, 2007; Chu and Chapleau, 2010; El Mahrsi *et al.*, 2014; He *et al.*, 2020). These studies mostly covered the data-mining procedure but did not capture the user's actual activity-travel patterns, with a few exceptions (e.g., Goulet-Langlois *et al*., 2016). Also, the insights on activity-travel patterns were derived either from Australian, Asian, Canadian, or European contexts. Thus, our knowledge of activity-travel patterns and tour formation of transit users in the US context has been limited. Our goal in this study was to address this research gap.

More specifically, this study investigated the complex activity-travel patterns and tour formation of transit users. Here, the term *pattern* referred to a complete sequence of activities (in-home and out-home) and trips made by an individual over a full day whereas *tour*, a basic unit of a full pattern, was defined as a sequence of trips that begins and ends at the same location (here, at home) and contains single or multiple activities. Tours can be constructed with different degree of complexity based on how many different activities are involved in a tour (more precisely how many non-home locations a tour entails). A *simple* tour started and ended at home and includes a single non-home activity. If the activity performed was work, then it was a *simple work* tour; for any other activity type, it was a *simple non-work* tour. On the other hand, a tour containing more than one non-home activity location was defined as a *complex* tour. If all non-home activities were work, then the tour was a *complex work* tour; if all the non-home activities were non-work, then the tour was a *complex non-work* tour. Complex tours can also combine work and non-work activities in the same tour, in which case they were deemed *work-non-work mixed* tours (Rafiq and McNally, 2020a). The detailed classification of tours are shown in Figure 1a and Figure 1b.

Figure 1. Defining simple and complex tours



Since work activities are less flexible, employed people with a non-home work activity typically made at least one work tour (either work-only or work-nonwork mixed) and then aligned their non-work activities with respect to that tour. Non-work activities could be performed as separate non-work tours or as a part of a work-nonwork mixed tour, in five ways:

1. before work: non-work performed before starting the first work tour of the day by making a non-work (simple or complex) tour
2. way to work: when an individual has started his work tour but did not yet reach the workplace and performed non-work activities on the way
3. during work: non-work activities that are performed outside workplace but the person returned to workplace after completing them
4. way to home: non-work activities that are performed as the person is on his way to home from the workplace but has not reached home yet
5. after work: non-work activities that are performed by making separate non-work tours after returning home from work.

This report is organized as follows. Chapter 1 discusses the relevant literature on transit users. Chapter 2 describes the data and sample used in the research and present detailed trip characteristics and tour formation (particularly work tours) of transit users. Chapter 3 outlines the activity-travel patterns of transit users and transportation disadvantaged groups. Chapter 4 summarizes the factors that govern the choice of a particular type of work tour. Conclusions, limitations, and policy implications are discussed in Chapter 5.

Chapter 1: Literature Review

This section provides an overview of previous literature that focused on transit users' demographics, travel characteristics, and trip chain behavior.

1.1 Socio-demographic and Travel characteristics of Transit Users

In a recent study, the APTA (2017) summarized the dominant characteristics of transit users as aged between 25 to 54 years (79%), employed (71%); belonging to a 1- or 2-person household (57%); women(55%); and white (40%);. It has been observed that ethnic minority groups depend more on public transit than the white population (Grahn et al., 2019). Differences in socio-demographic characteristics were observed between bus and rail riders. For example, the level of education of rail riders was greater than that of bus riders (70% versus 42% who have at least a bachelor's degree) and rail riders were more likely to be employed than their bus rider counterparts. Household income of rail riders tended to be higher than for bus riders (Taylor and Morris, 2015; APTA, 2017; Grahn et al., 2019; Buehler and Pucher, 2012). Since rail riders have higher household incomes and thus have a greater availability of vehicles, they thus have a higher chance of having a driver's license than bus riders. While rail riders were more likely to be white than black, bus riders had an equal distribution between these racial groups (APTA, 2017).

In addition to the differences between bus and rail riders, heterogeneity among transit users might exist due to the variation in trip characteristics, daily activity-travel patterns, tour formation attributes, attitudes, preferences, transit service quality, and residential location attributes. In previous studies, heterogeneity was observed based on transit users' attitudes and preferences toward transit (Zhou et al., 2004; Iseki and Smart, 2012; Krizek and El-Geneidy, 2007), residential neighborhood types and users' attitudes (Namgung and Akar, 2015), spatial and travel behavioral features (Ou and Cai, 2018), and user characteristics and service quality (Bordagaray et al., 2014).

The socio-demographic and travel characteristics of various transit disadvantaged groups, such as senior citizens, low-income households, and people living in rural areas were also considered in prior studies. For example, Yang and Cherry (2017) examined the socio-demographic characteristics of rural transit users and observed that these users tended to be non-white, captive riders (had difficulty in finding alternative transport modes), had lower personal and household income, and owned fewer cars. Giuliano (2005) observed the role of transit in the travel behavior of low-income households and found that these households were auto-dependent rather than transit-dependent (transit was used only for a small portion of their travel). The limited availability and lack of service quality made transit a poor substitute for a private vehicle for these households. Those who used transit regularly had the lowest level of mobility among all population segments. The use of public transit among older adults was explored by Hess (2009) who found that older adults who are male, non-white, and belong to low-income households were more likely to make frequent transit trips.

Next, we discuss some major characteristics of transit trips. According to APTA (2017), public transit was predominantly used to travel to or from the workplace (49% trips). The second most frequent trip purpose was shopping (21%). While rail riders were more likely to indicate their trip purpose as getting to or from work, bus riders were more likely to use transit for traveling to or from school, medical or dental appointments, or other purposes (e.g. picking up a car from service appointments, business appointments). The majority of riders used transit five days per week. Most of these users (more than two-thirds) chose to walk either to access a station (access) or to reach a destination (egress).

Identifying gaps from previous literature

Despite the complexity of an individual's activity-travel patterns, the overall transit user population may fall into a small number of heterogeneous sub-groups, each with a defined representative activity-travel pattern. However, previous studies did not consider such heterogeneity in terms of user trips or tour/pattern characteristics nor in a combination with their demographics. Identification of potential transit market groups with representative daily activity-travel patterns may help transit operators to understand user demand for activities as well as travel and to implement market strategies that address a particular group of users to meet their travel needs and to improve quality of service. Prior research examined the socio-demographic and travel characteristics of selected groups of transit disadvantaged groups. However, these studies did not focus on the full activity-travel patterns of these groups, an aspect that is likely very important in understanding activity-travel needs over various periods of the day.

1.2 Trip Chain Behavior of Transit Users

Prior works that considered trip chaining or tour behavior of transit users focused on a variety of issues. Hensher and Reyes (2000) found in Sydney, Australia that the likelihood of public transit usage decreased with the change of a tour from simple to complex. Based on a limited number of socio-demographic variables, they regressed the utility of a simple and complex tour (work or non-work) associated from either car or public transit usage. Krygsman et al. (2007) investigated, in the context of the Netherlands, the causal relationships between travel mode choice (car or public transit) and the insertion of intermediate activities before, in between, or after a work activity within a work tour. The authors concluded that the inclusion of an intermediate stop for non-work activity before or after work tended to decrease public transit utility but increased car utility. Moreover, they found that for home-based work tours, activity decisions were made before deciding travel mode whereas Islam and Habib (2012) observed that trip chaining and mode choice decisions were made simultaneously for work tours. Yun et al. (2014) observed a negative association between the complexity of trip chains (measured by stop frequency) and transit usage for work tours in Zhongshan, China.

In contrast, Currie and Delbosc (2011) found in Melbourne, Australia that trip chains made by public transit appeared more complex than those undertaken by car particularly for non-work tours. However, the opposite relationship was found for work tours. Primerano et al.

(2008) observed that in Adelaide, Australia all forms of mass public transport tours involved a higher numbers of activities compared to private car-based tours. The authors argued against the hypothesis of Hensher and Reyes (2000) that public transit is not flexible for complex trip chaining. They instead suggested that the nature of complex trip chaining behavior for public transit users is different rather than inflexible. With public transit, users can access destinations comprising a mix of land uses in close proximity to one another whereas travelers using a private car can access activities located at multiple destinations that are not necessarily close to each other. This statement was reinforced by Ho and Mulley (2013). Based on the Sydney Household Travel Survey data, the authors showed that public transit usage in tours increased as the number of activities located in close proximity to one another chained into a tour increased (yielding a multiple purpose single destination tour). These results suggested that chaining multiple activities in tours does not necessarily hinder public transit usage but an unfavorable spatial distribution of activity locations might do so.

By challenging the traditional notion of a positive association between car usage and the complexity of trip chaining and identifying the importance of regional variability in trip chain behavior, Susilo and Kitamura (2008) suggested that in Osaka, Japan transit commuters tended to chain trips more often and make more stops than car commuters. Based on onboard transit ridership survey data collected in Indiana and Ohio, US, and the results of univariate analysis, Bernardin Jr et al. (2011) suggested that transit tours were at least as complex as tours by other modes. They also found that the complexity of transit work tours was highly dependent on income and vehicle ownership of the commuter, for instance, low-income transit commuters were observed to make more complex tours than affluent commuters.

Identifying gaps from previous literature

In summary, previous studies only addressed the interrelationships between the complexity of activities and the utility of alternate mode usage with a primary focus on private vehicles and public transit. In recent years, many studies have been conducted (using data from China, Canada, Australia, and Europe) focused on techniques for extracting information on transit riders' daily activity-travel patterns by mining transit smart card data (Ma et al., 2013; Ma et al., 2017; Bhaskar and Chung 2014; Morency et al., 2007; Chu and Chapleau, 2010; El Mahrsi et al., 2014; He et al., 2020). These studies mostly covered the data-mining procedure but did not recognize the riders' actual activity-travel patterns with few exceptions (e.g., Goulet-Langlois et al., 2016). Moreover, these insights on transit activity-travel patterns or trip chain behavior were derived either from Australian, Asian, or European contexts. Therefore, our knowledge of travel behavior of transit users from an activity- or tour-based perspective in the US is rather limited.

1.3 This Study in the Context of Previous Literature

The purpose of this study was to perform an in-depth analysis of the activity-travel patterns and tour formation of transit users in the US context. More precisely, our research goals were as follows:

- To analyze *how* and *when* public transit users incorporate different non-work activity demands within their work tours, constrained by work time commitments, transit operating characteristics, and access/egress issues.

- To develop a tour choice model to characterize public transit commuters (*who*) based on the complexity of work tours and to assess the impacts of various demographic, location, and activity-travel factors on the likelihood of a transit commuter to choose a particular type of work tour (*why*).

- To identify latent classes of transit users based on the *heterogeneity* in daily activity-travel patterns and tour formation.

- To analyze the activity-travel patterns of transit *disadvantaged* groups, such as zero vehicle owners, older adults, low-income households, and people living in rural areas.

Chapter 2: Empirical Analysis of Tours Utilizing Transit

Public transit usually offers less flexibility and mobility services than a private car in chaining activities due to temporal and spatial constraints such as fixed routes and schedules, transfer requirements, waiting times, and access/egress issues. Its broader adoption and usage are arguably dependent on its ability to offer effective chaining of activities and trips. To better understand the demographic, trip, and tour characteristics of transit users, we explore tour formation and the overall activity-travel patterns of transit users via comprehensive univariate analyses, which are presented in the following sections.

2.1 Transit Users and Transit Commuters: Data and Sample

The 2017 National Household Travel Survey (NHTS) provides information on travel by US residents in all 50 states and the District of Columbia (Federal Highway Administration, 2017), including data on trips made by all modes of travel (private vehicle, public transportation, pedestrian, biking, etc.) and for all trip purposes (travel to work, school, recreation, etc.). The dataset contains the following four data tables:

- Households (socio-economic and location characteristics of surveyed households)
- Persons (demographic characteristics of all household members)
- Trips (over 24-hours by all household members 5 or older and trip-related attributes)
- Vehicles (vehicles used by the responding households)

The NHTS dataset contains 129,696 households consisting of 264,234 persons who took a total of 923,572 trips. For this study, we identified *public transit users* as those individuals who start their first trip from home and end their last trip at home and who used public transit for at least one trip segment[1]. A choice of travel mode is treated as public transit if it is any of the following: public or commute bus, city-to-city bus, subway/elevated/light rail/streetcar, and Amtrak/commuter rail. This yields a final sample of 4,994 individuals who made a total of 20,222 trips where almost half of the trips are made by transit (10,011). We identified *transit commuters* as those individuals who are at least 18 years old, perform at least one work activity, and used public transit in at least one trip segment within their home-based work tours. This resulted in a subsample of 2,448 individuals. Home-based work tours are formed by linking person trip sequences that start and end at home and contain at least one work activity. The result was a total of 2,454 home-based work tours.

2.2 Demographics of Transit Users

Who are domestic public transit users? Table 2.1 summarizes household, personal, and location characteristics of selected transit users who used a transit mode for at least one trip segment.

[1] When a trip involves a change of modes, each mode defines a trip segment.

Table 2.1 Descriptive statistics of transit users (N = 4,994)

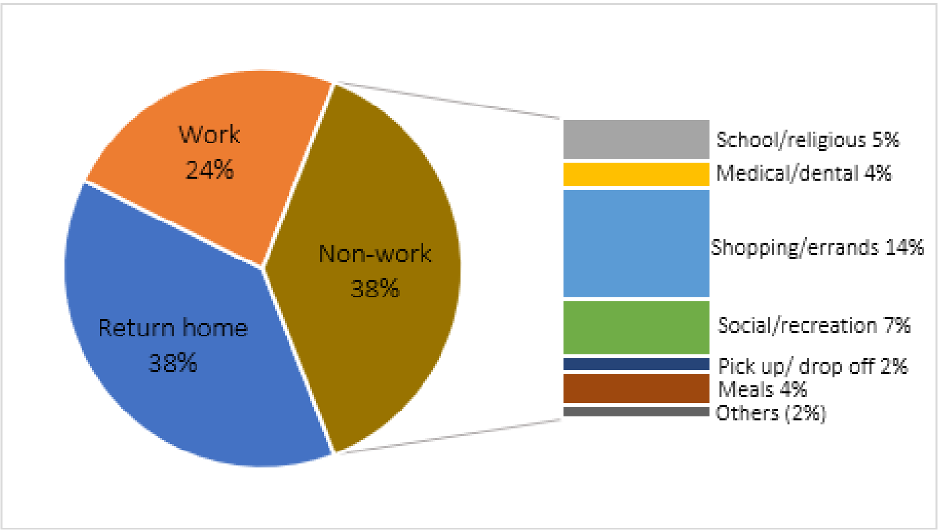
Variables	Percentage of users (%)
Household characteristics	
Household size	
Household size = 1	29.4
Household size = 2	34.7
Household size > 2	35.9
Number of household vehicles	
Number of vehicles = 0	36.2
Number of vehicles = 1	29.7
Number of vehicles > 1	34.1
Monthly household income (USD)	
Low income (less than $35K)	37.3
Middle income ($35K to $100K)	29.2
High income ($100K or more)	31.2
Presence of child aged 0-17	19.0
At least one vehicle per licensed driver	48.1
Personal characteristics	
Age groups	
Younger group (below 18 years)	6.6
Millennials (18 – 38 years)	33.8
Generation X (38 – 58 years)	32.3
Older adults (more than 58 years)	26.1
Gender: Male	48.6
Employment status: Employed	62.2
Race: white	59.3
Type of transit use	
Commuter rail	42.7
Public bus	62.4
Location characteristics	
Population density (persons per sq. mile) in census block group	
Low density (0-2000)	17.1
Medium density (2000-10000)	42.5
High density (>10000)	40.4
MSA has a rail connection	50.7

In terms of household characteristics, a majority of transit users have more than two persons per household (35.9 percent) and belong to a lower income group (annual income less than $35K USD) (37 percent). Few of these households have children aged 17 years or lower (19 percent) and 51.9 percent are car deficient households (less than one car per licensed driver). The age distribution of transit users is similar for millennials (18 - 38 years) and Generation Xers (38 - 58 years) and there is a considerable fraction of older adults among users (26 percent). Most of the transit users are White (59.3 percent), employed (62.2 percent), and live in medium to high-density areas.

2.3 Trip Characteristics of Transit Users

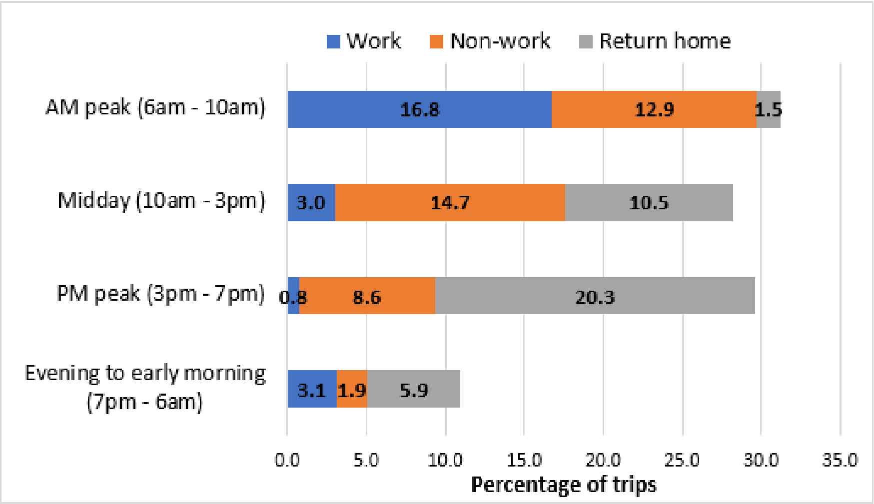
What are the characteristics of individual trips made by transit users? Figure 2.1 shows that transit is utilized for a considerable fraction of work (24 percent) and return home trips (38 percent). Shopping or running errands (14 percent) is also a common trip purpose of transit. Only 5 percent of trips are made by transit to go to school or religious activity. Note that we did not consider school bus as a public transit category. Transit is occasionally used for transporting someone (pick up/drop off) or going to a restaurant or medical facility.

Figure 2.1 Distribution of transit trips by activity purposes



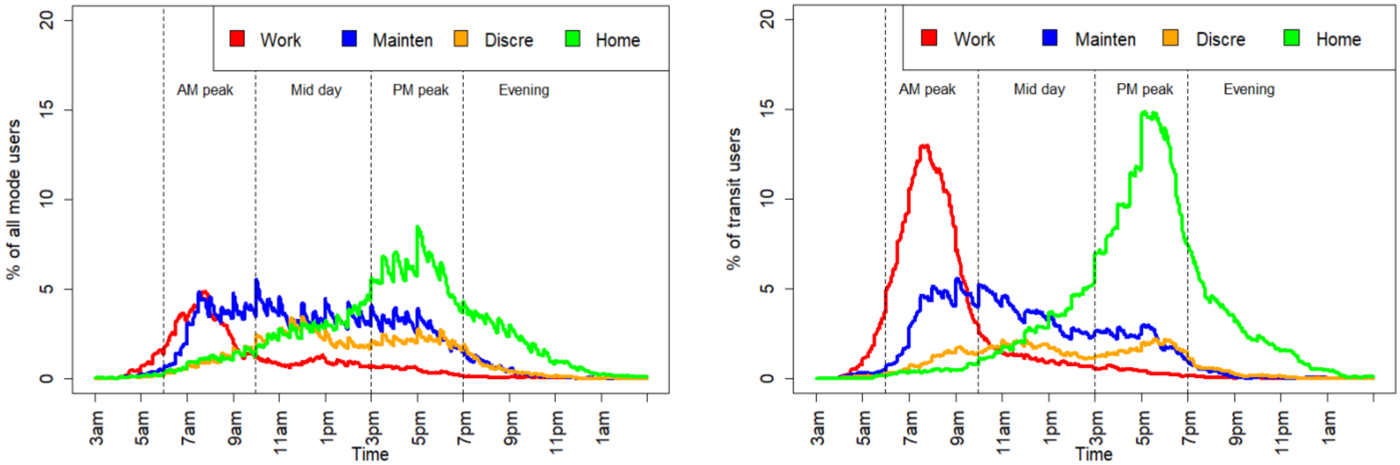
Next, we investigate how the demand for transit trips for three activity purposes -- work, non-work, and return home -- varies over time-of-day. Figure 2.2 shows that the overall demand for transit, represented by the fraction of trips made by transit, is similar (about 30 percent) for all conventionally defined time periods during daytime (i.e., AM peak, midday, and PM peak period). Trip purpose, however, varies among these three time periods. For example, during the AM peak period (6 am – 10 am), a majority of transit trips are made for work purposes (about 17 percent) whereas the higher fraction of midday (10 am – 3 pm) trips are made for non-work purposes (15 percent), and the dominant share of PM peak (3 am – 7 pm) transit trips represents return home trips (20 percent). Since transit services are typically unavailable or operate with lower frequency during the late evening through early morning (7 am – 6 am), it is not surprising to observe a lower fraction of transit trips (11 percent) during this period.

Figure 2.2 Distribution of trip purpose by time of day



The fraction of people traveling by activity purposes can be displayed in a *time in motion plot* in Figure 2.3 which compares travelers making trips by (a) *all modes* versus (b) *public transit-only*.

Figure 2.3 Time in motion plot by trip purpose

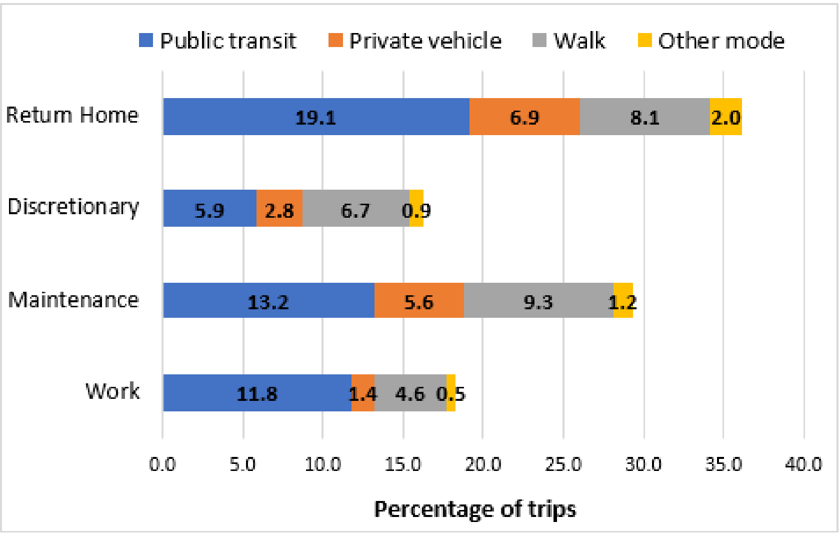


(a) Traveler by *all modes* (b) Traveler by *public transit*

Note that we categorize trip purposes into four groups: (1) work: work- and work-related trips; (2) maintenance: school/daycare/religious activity, medical/dental services, buying goods, buying services, other general errands, and drop off/pick up someone; (3) discretionary: go out for a meal, snack, carry-out, recreational activities, and visiting friends or relatives; and (4) return home. Figure 2.3 shows that travelers typically commute to work during the AM peak period and return home during the PM peak period (Figure 2.3a). Transit riders demonstrate a similar trend but with higher peaks (Figure 2.3b). The higher peaks for work and return home trips indicate that among transit riders, the majority of travelers are employed and use transit regularly, primarily for work and return home purposes. Maintenance trips are observed to occur at a constant rate throughout the day except in the evening period (Figure 2.3a). When travelers use transit for maintenance purposes, a similar trend is observed with a slight variation in the late midday and PM peak periods (Figure 2.3b). For discretionary trips, no prominent difference appears between trips made by all modes and trips by transit-only.

Mode use behavior of transit users by trip purposes is shown in Figure 2.4. For any trip purpose, the majority of trips are observed to be made by public transit except for discretionary purposes. A similar fraction of trips (about 12-13 percent) is reported to be made by transit for both work and maintenance purposes. The second most frequent mode used by transit users to access any activity is walking, followed by private vehicles.

Figure 2.4 Distribution of travel mode by trip purpose



2.4 Demographics of Transit Commuters

Table 2.2 summarizes the household, personal, and location characteristics of the selected transit commuters who used a transit mode in at least one trip segment of the full home-based tour. In terms of household characteristics, transit commuters had on average two persons per household, 77 percent had a car available (42 percent have more than one) and 44 percent belonged to a higher income group (annual income exceeds $100K USD). A majority were car sufficient households (57 percent had at least one vehicle per licensed driver) but few of these households had children aged less than or equal to 17 years (16 percent). The age distribution of transit commuters was similar in number for millennials (18-38 years) and non-millennials (above 38 years) and males and females were an equal share of transit commuters. Most transit commuters were White (66 percent), worked full-time (84 percent), had flexibility in work arrival time (53 percent), and lived in metropolitan areas that have rail connections (59 percent), relatively few in the sample were Hispanic (11 percent), immigrants (23 percent), or had multiple jobs (8 percent).

Table 2.2 Descriptive statistics of transit commuters

Variables	Mean	Std. Dev.
Total respondents	2,448	
Household characteristics		
Household size	2.42	1.26
Number of household vehicles		
Number of vehicles = 0	0.23	0.42
Number of vehicles = 1	0.35	0.48
Number of vehicles > 1	0.42	0.49
Monthly household income (USD)		
Low income (less than $35K)	0.21	0.40
Middle income ($35K to $100K)	0.35	0.48
High income ($100K or more)	0.44	0.50
Home ownership (Own = 1, Others = 0)	0.54	0.50
Presence of child aged 0-17 (Yes =1, No = 0)	0.16	0.37
Number of adults	2.03	0.87
At least one vehicle per worker (Yes =1, No = 0)	0.56	0.50
At least one vehicle per licensed driver (Yes =1, No = 0)	0.57	0.50
Personal characteristics		
Age groups (Millennials: 18-38 yrs. = 1, Others = 0)	0.43	0.50
Gender (Male =1, Female = 0)	0.51	0.50
Type of employment (Full time=1, Part time=0)	0.84	0.37
Flexibility in work arrival time (Yes=1, No=0)	0.53	0.50
Multiple job status (Yes=1, No=0)	0.08	0.28
Occupation (Prof., managerial or technical = 1, Others = 0)	0.62	0.48
Education (at least some college degree = 1, Others = 0)	0.87	0.34
Hispanic or Latino status (Yes = 1, No = 0)	0.11	0.31
Race (White = 1, Others = 0)	0.66	0.47
Immigration status (Yes = 1, No = 0)	0.23	0.42
Employment status of spouse or partner		
Has employed spouse or partner	0.48	0.50
Has non-employed spouse or partner	0.12	0.32
No spouse or partner	0.40	0.49
Captive rider: no vehicle or no driving license or give up driving for medical condition (Yes=1, No=0)	0.34	0.47
Location characteristics		
Population density (persons per sq. mile) in census block group		
Low density (0-2000)	0.18	0.38
Medium density (2000-10000)	0.41	0.49
High density (>10000)	0.41	0.49
MSA rail status (Have rail = 1, Does not have rail or household not in MSA = 0)	0.59	0.49
Distance from home to workplace (mile)	21.89	110.05
Proximity to transit station		
Trip time to transit station (min.)	9.72	8.79
Trip time from transit station (min.)	12.52	14.63

2.5 Trip and Tour Characteristics of Transit Commuters

A *tour* is a sequence of trips that starts and ends at the same location and contains one or more activities performed at single or multiple destinations. If the starting and ending location in question is home, the tour is deemed a home-based tour. Since our study involves working individuals, we are interested in home-based tours that contain at least one work location outside home. These are called home-based *work* tours. A home-based work tour is called a *simple work tour* if it contains only one work activity but no non-work activity, thus having an activity sequence of Home-Work-Home.

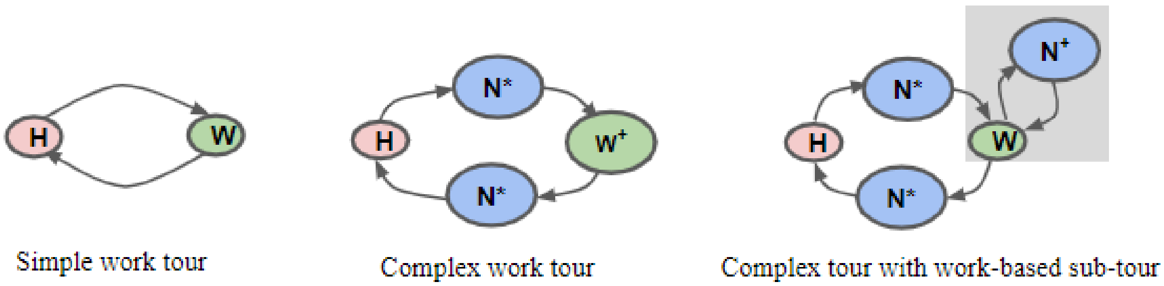
A home-based work tour may also contain non-work activities. These tours are called *work-nonwork mixed* tours. Here, these mixed tours are subdivided into complex work tours and complex tours with a work-based sub tour. *Complex work tours* contain non-work locations accessed on the way to ('way to work') or from work ('way to home'). Multiple work locations can be visited on a tour and these are also considered in this tour category.

Work-based tours involve visiting non-work locations 'during work' (such as during a lunch break). When a home-based tour is combined with a work-based tour, we refer to as *complex tour with a work-based sub-tour*. Both simple and complex work tours have exactly one circuit whereas complex tour with work-based sub-tour has two or more circuits: one circuit between home and work, and (at least) one circuit with work as a base.

Figure 2.5 shows the general construct of these tour types, with the type differences emanating from the degree to which non-work activities are mixed with work. For instance, simple work tours do not involve any non-work at all, complex work tours involve non-work stops on the way to work and/or on the way to home, and work-based tours can have non-work stops in any or all of these three ways. To represent the different types of tours, we produced a graphical model where activity locations are vertices labeled as H (home), N(non-work) and W (work) depending on where the activity is performed and an arrow between two vertices denotes a trip between the corresponding locations.

A tour type is a generic representation of performing work and non-work activities and can be realized in many possible ways. Any specific realization of a tour of a certain type is called a *tour pattern* or simply a *pattern*. For example, H-W-H is a pattern of realizing a home-based simple tour (which happen to be the *only* pattern for this particular type) and H-N-W-H and H-W-N-N-H are sample patterns of home-based complex tours that involve one non-work on the way to work and two non-work activities on the way to home. As a mean of representing patterns of any kind, we denote each pattern as a 3-tuple (*a*, *b*, *c*) where the three whole numbers (including zero) indicate the number of non-work activities involve on the way to work, on the way to home, and from work and back to work respectively. Hence, the three patterns mentioned can be denoted as (0, 0, 0), (1, 0, 0) and (0, 2, 0), respectively. We used this notation when we identify the most dominant tour patterns from data for our study group.

Figure 2.5 General construct of home-based work tours



N*: zero or any number of non-work
N+: one or more non-work
W+: one or more work
Shaded portion can repeat

After extracting tour attributes from the data, we identified which work tour patterns appeared most frequently. To ensure a sufficient sample of at least 50 observations in each pattern, we identified seven dominant patterns that represented 80 percent of the total work tours. The remaining 20 percent of these tours were labeled as "other." Figures 2.6 and 2.7 display the identified seven patterns. The simple work tour was deemed pattern 1. Those patterns that represents complex work tours were deemed pattern 2, with four sub-categories deemed as patterns 2a, 2b, 2c, and 2d based on the order of non-work activities. Last, complex tours with a work-based sub-tour were deemed as pattern 3, with two sub-categories patterns (patterns 3a and 3b). We also identified a complex tour pattern comprising 70 observations (2.8 percent of the total). This pattern included two work but no non-work activities. Since NHTS data does not provide location data, it was not possible to identify the precise nature of these work activities. Therefore, these tours were considered in the “other” category.

Figure 2.7 shows the fraction of tours for each of the three primary pattern types. The largest group were simple work tours (49 percent). Complex work tours constituted the next most frequent group (32 percent) with sub-category patterns 2a and 2b (33 and 15 percent). This suggests that travelers who perform non-work activities as part of a work tour tended to do so primarily on the way home from work. Among all pattern types, complex tours with a work-based sub-tour comprised 19 percent of all HBW tours, with patterns 3a and 3b constituting 43 percent and 13 percent of these tours, respectively.

Figure 2.6 Seven dominant patterns of work tours: simple work tours (1), complex work tours (2a, 2b, 2c, 2d), and complex work tours with work-based sub-tours (3a, 3b)

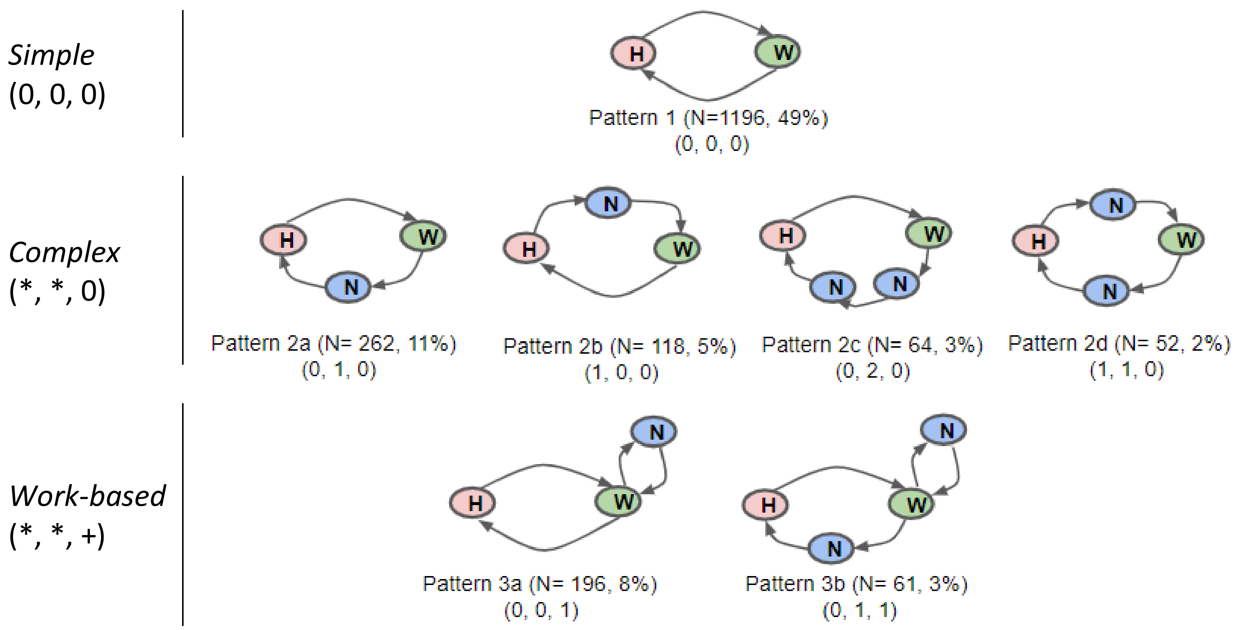
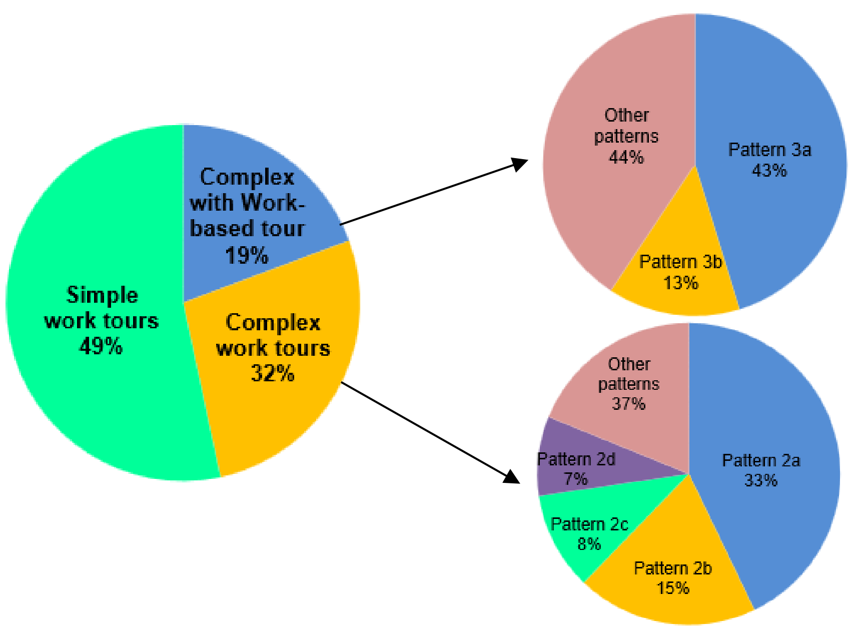


Figure 2.7 Fraction of different work tours



Pacific Southwest Region UTC
University Transportation Center

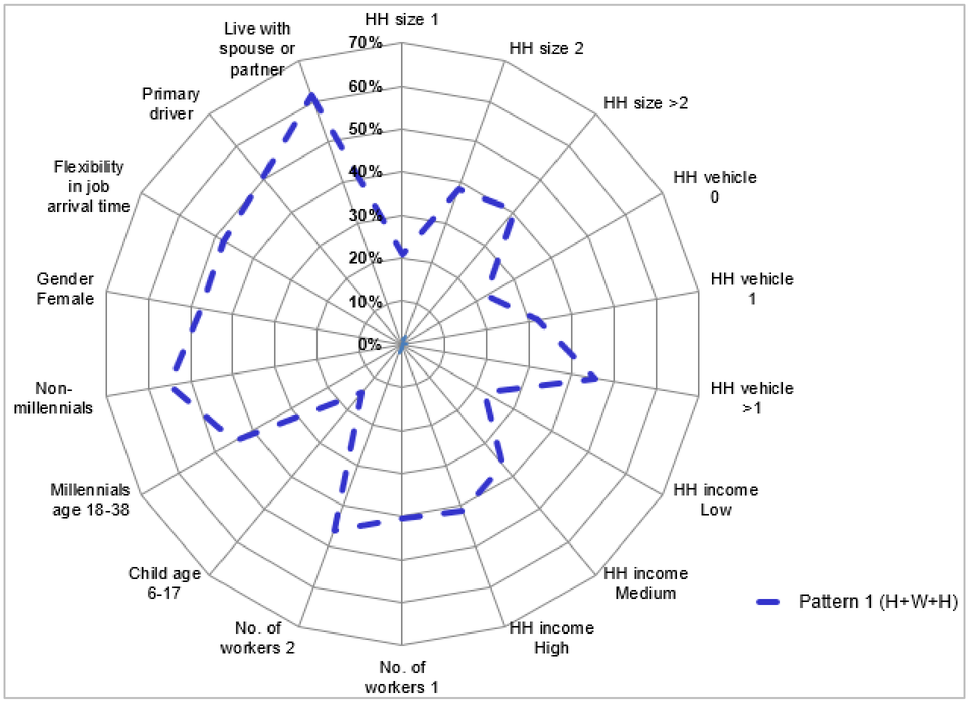
2.5.1 Simple work tour

This section discusses the socio-demographic and travel characteristics of travelers making simple work tours.

2.5.1.1 Socio-demographic characteristics

The distribution of socio-demographic characteristics of travelers who make simple work tours is shown in the spider plot in Figure 2.8. The prevailing socio-demographic characteristics in this category of tours were males living with spouse or partner who belong to households that have at least two workers and no children (aged between 6 and 17) and have more than one vehicle (the respondent being the primary driver of one of those vehicles). These individuals reported less flexibility regarding work arrival time.

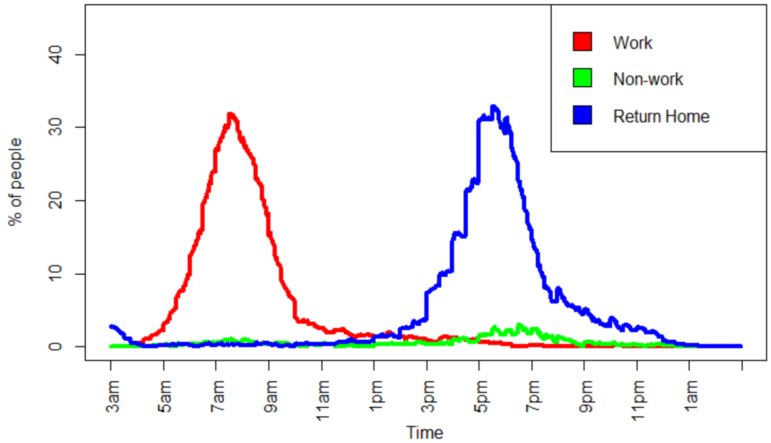
Figure 2.8 Socio-demographic characteristics of travelers in simple work tours



2.5.1.2 Temporal distribution of trips

The temporal distribution of activities, or 'time in motion' of travelers, for pattern 1 is displayed in Figure 2.9. The figure shows the fraction of respondents who traveled to a work, non-work, or return home activity by time-of-day. Note that the figure covers *all* trips made in an entire day, not only the work tour trips. While simple work tours do not include non-work activities, such activities could be part of home-based non-work tours performed either before or after the work tour. For simple work tours, such non-work purposes can be seen in the PM peak and evening periods.

Figure 2.9 Time in Motion for three activity purposes in simple work tours



2.5.1.3 Modal distributions

Each simple work tour had two trips: from home to work and from work to return home. Table 2.3 shows the distribution of tours by travel mode for these tours. The table also shows the mean travel time for the associated mode. Note that a trip may have multiple travel modes; if so, the *primary* mode (which had the highest proportion of travel time) is reported in the table. We observe that public transit was predominantly used in both legs of most simple work tours (in about 90 percent of these tours). A small fraction of tours had both trips made by private vehicles (~5 percent) or on foot (~1 percent).

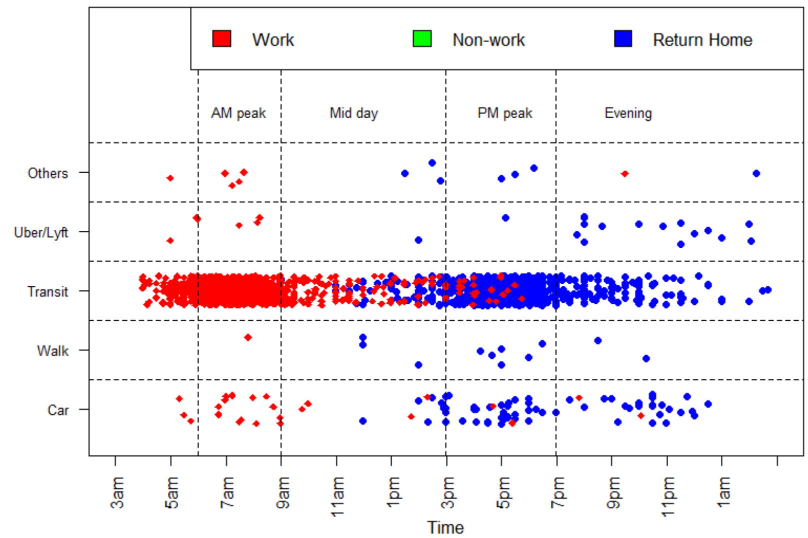
Table 2.3 Percentage of tours and average duration for trip modes in simple work tours

	H-W-H (n= 1196)			
	Fraction of tours		**Mean travel duration (min.)**	
	H-W	W-H	H-W	W-H
Single mode	97.6	97.1	---	---
Multiple modes	2.4	2.9	---	---
Primary mode *				
Public transit	92.9	88.7	62.8	68.6
Walk	0.3	1.3	37.3	32.1
Private vehicle	5.3	7.9	16.4	24.5
Ride-hailing	0.7	1.3	34.0	29.1
Other	0.9	0.8	46.5	48.7

*Notes: Home-based work tours were identified by individuals who used transit in at least one trip segment. * If multiple modes were used in a trip, only the primary mode was reported.*

Now that we identified which trips were made by which modes, we examined when those trips started and how they spanned a 24-hour day. Figure 2.10 plots trips color-coded by trip purpose with the x-axis showing departure time of day and the y-axis showing the mode used. Furthermore, dots are color coded based on the purpose for which the trip was made (red for work, green for nonwork and blue for returning home). The horizontal axis is also segmented into conventional travel periods: AM peak (6 am to 9 am), Midday (9 am to 3 pm), PM peak (3 pm to 7 pm), and Evening (after 7 pm). Notice that for simple work tours, transit demand was higher in both the AM and PM peak periods. Transit departure times tended to be earlier than for other modes (at least for travelers who used transit for at least one trip on a work tour).

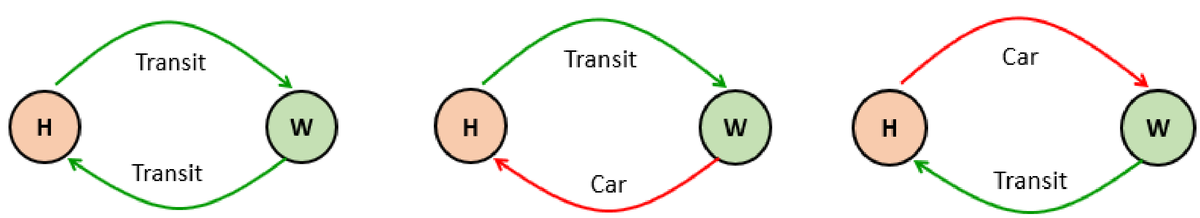
Figure 2.10 Modal distributions by three trip purposes in simple work tours



2.5.1.4 Modal sequence by tour

While the preceding discussion focused on mode use for each trip independently, we now consider mode usage as a *sequence* within a tour to illustrate how transit commuters connect modes in their work tours. For this, we represent the modes chosen in all trips in a sequence diagram such as shown in Figure 2.11. Instead of showing all sequences that may exist for tours of a certain pattern (which could be fairly large for tours involving multiple trips), we counted how many times a given modal sequence appears and report only the top three frequent sequences.

Figure 2.11 Frequent modal sequences in simple work tours



Most frequent sequence (83% tours)

Second-most frequent sequence (5% tours)

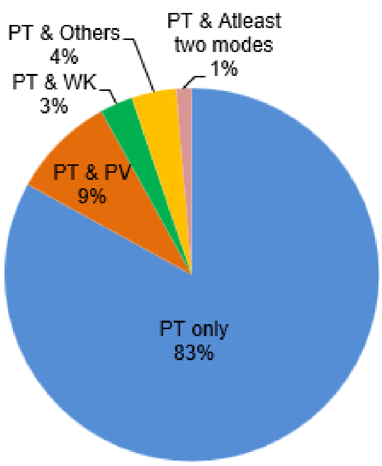
Third-most frequent sequence (1% tours)

The top three frequent modal sequences for simple work tours were (transit, transit), (transit, car), and (car, transit) that constitute about 83 percent, 5 percent, and 1 percent of tours, respectively, as shown in Figure 2.11. That means, in about 83 percent of home-based simple tours, transit was used for both the work-bound and home-bound trips, nearly 5 percent of tours involved transit in the first trip and private vehicle in the return leg, and about 1 percent of tours involved the reverse mode choice. In the latter two modal sequences, travelers reported being car passengers, which denotes a pick-up or drop off by family members or friends. On average travel by transit took about 63 minutes to work in the morning peak period and about 69 minutes to return home in the evening peak period, as compared to 16 minutes and 25 minutes by private vehicle, respectively (cf. Table 2.3).

2.5.1.5 Frequency of transit with other modes

Next, we were interested in examining the frequency of transit use with other travel modes at an aggregate level. Figure 2.12 depicts a pie chart for simple work tours, each of which used transit for at least one trip segment. Transit was also used in combination with walk (PT&WK), private vehicle (PT&PV), other modes (excluding walk and private vehicle, PT&Others), or any two or more combinations of modes. The share of transit only tours (PT only) dominates (83 percent) for simple work tours.

Figure 2.12 Frequency of transit with other modes in simple work tours



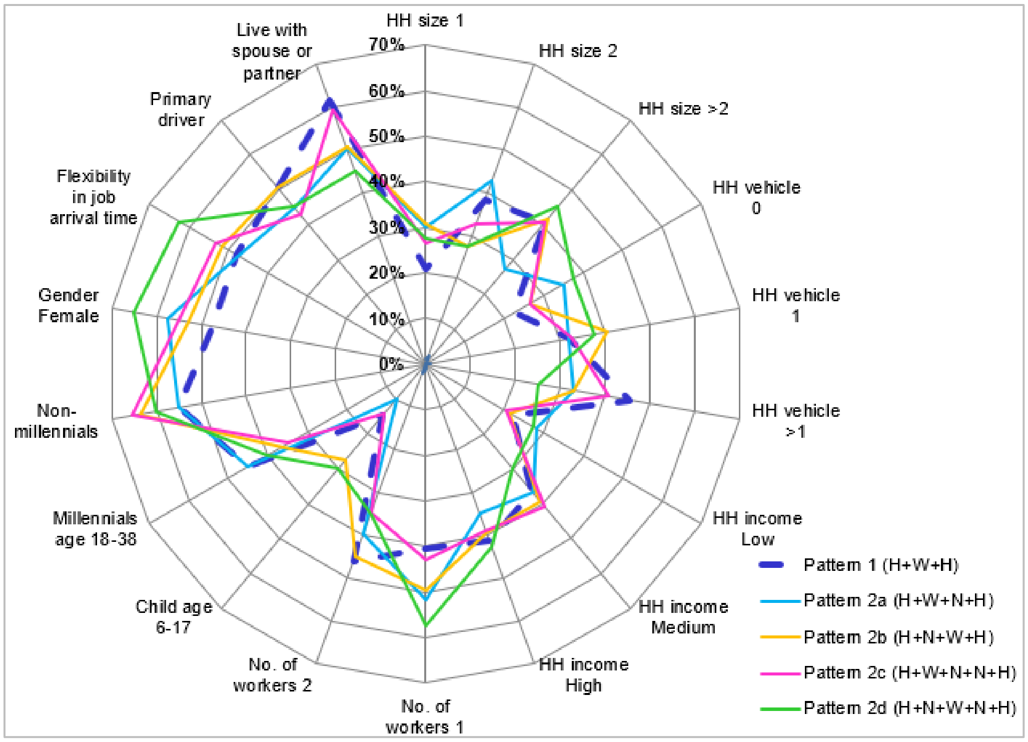
2.5.2 Complex work tour

For complex work tours, four dominant patterns (2a, 2b, 2c, and 2d) were identified. This section represents the properties of each of the identified patterns.

2.5.2.1 Socio-demographic characteristics

Figure 2.13 depicts the distribution of socio-demographic characteristics for complex tours (pattern group 2) relative to simple tours (pattern 1). Travelers who made complex work tours were most typically females with medium or high income. They reported more than two members in their household, were typically the only worker in the household, and had flexibility in their work arrival time. Their households tended to have at least one vehicle but the traveler was not considered the primary driver of that vehicle. They reported having more children between 6 and 17 years of age in their household compared to simple tour makers. A higher percentage of this group of travelers belonged to the non-millennial group (age > 38 years), and a lower percentage reported living with a spouse or partner.

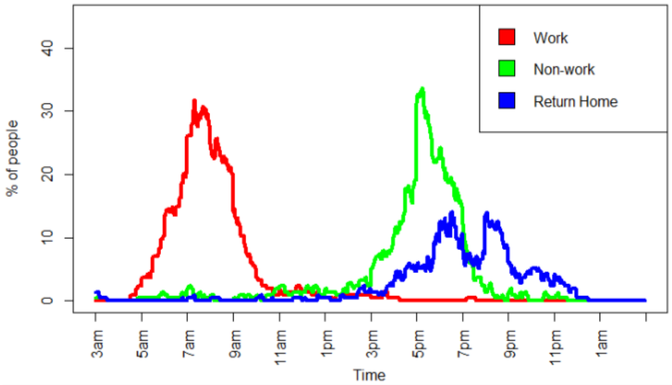
Figure 2.13 Socio-demographic characteristics of travelers in complex work tours



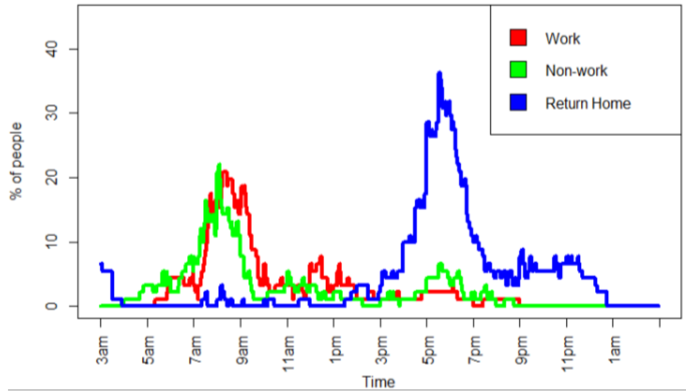
2.5.2.2 Temporal distribution of trips

The time in motion plots for complex work tour makers are shown in Figure 2.14. Conventional temporal patterns defined by individual activity starting times are identifiable in the first few figures but the distributions for more complex tours clearly illustrate the chaining effects before or after a work activity. An earlier initial departure time from home by travelers who made non-work activities before the work activity (patterns 2b and 2d) is shown in Figure 2.14. Of interest, complex tours with one non-work stop on their return home (pattern 2a) had a bimodal distribution of return home times, peaking between 6 pm and 8 pm. This suggested that some travelers also had a home-based non-work tour that was performed after the work tour.

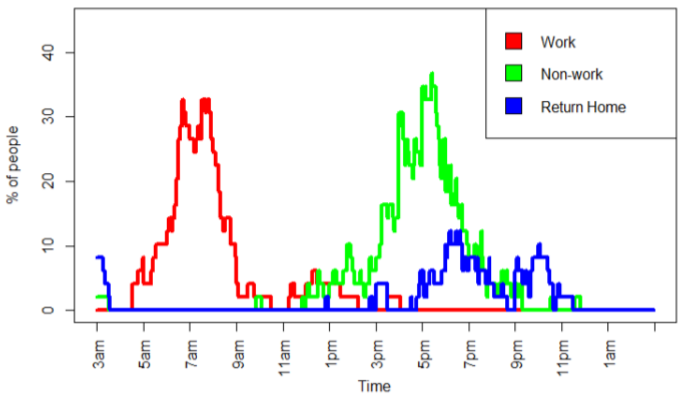
Figure 2.14 Time in Motion for three activity purposes in complex work tours



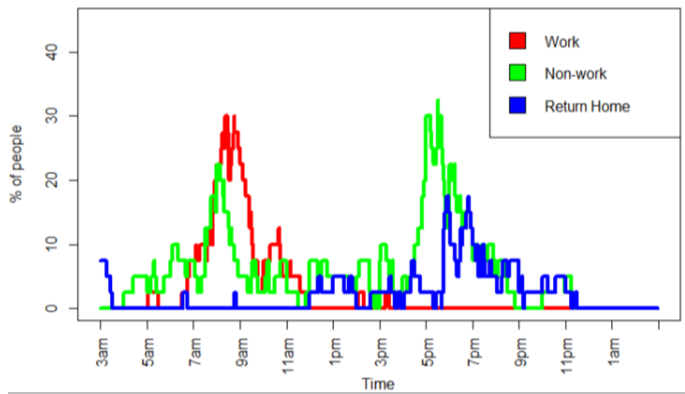
2a. H-W-N-H (n= 262)



2b. H-N-W-H (n= 118)



2c. H-W-N-N-H (n= 64)



2d. H-N-W-N-H (n= 52)

2.5.2.3 Non-work activity type and duration

A complex work tour may involve multiple trips and one or more non-work activities. To analyze these tours in depth, we examined the mode and travel duration for each trip in a tour as well as the activity purpose and duration for each non-work activity within the tour. Tables 2.4 and 2.5 present these results for the four identified patterns in group 2, including how non-work activity purposes and the amount of time spent on them differed across these patterns, particularly when non-work activities aligned themselves with respect to work. We focus on attributes of non-work activities and defer the discussion on modes to the next section.

For complex tours where travelers make a single non-work stop on the return home (pattern 2a), shopping (buying goods or services) was the most frequent activity (occurring in about 40 percent of these tours) and with an average duration of about 37 minutes. On the other hand, for non-work activity on the way to work (pattern 2b), the most common activities were pick up/drop off or buying a meal. Such activities were of shorter duration (about 6 minutes for pick up/drop off and about 11 minutes for buying meals) whether due to implied time constraints on the journey to work or simply the nature of these activities.

For travelers who performed two non-work activities on the return home (pattern 2c), most reported a shopping activity as the first non-work stop (on about 34 percent of tours), with the next most frequent non-work task being buying meals (in about 19 percent of tours). The same two non-work activity purposes dominated in the second non-work stop. With respect to activity duration, travelers spent on average of 26 to 48 minutes for shopping and about 57 to 72 minutes for buying meals (substantially greater than meals prior to work). This difference is likely due to both greater flexibility after work and the cultural nature of meals by time of day (with after work meals often involving family or friends).

Table 2.4 Percentage of tours for trip modes and non-work activities in complex work tours

	2a. H-W-N-H			2b. H-N-W-H			2c. H-W-N-N-H				2d. H-N-W-N-H			
	N = 262			N= 118			N = 64				N = 52			
	H-W	W-N	N-H	H-N	N-W	W-H	H-W	W-N	N-N	N-H	H-N	N-W	W-N	N-H
Single mode	97.3	96.2	98.1	99.2	93.2	97.5	100	98.0	100	96.9	98.1	96.2	98.1	96.2
Multiple modes	2.7	3.8	1.9	0.8	6.8	2.5	0.0	1.6	0.0	3.1	1.9	3.8	1.9	3.8
Primary mode*														
Public transit	89.7	64.8	35.2	45.8	57.6	72.9	85.9	54.7	23.4	26.6	38.5	61.5	76.9	23.1
Walk	3.4	16.1	20.7	23.7	28.8	6.8	3.1	15.6	23.4	18.8	26.9	28.8	13.5	32.7
Private vehicle	4.6	16.1	39.1	29.7	12.7	12.7	6.3	18.8	48.4	51.6	30.8	7.7	7.7	38.5
Ride-hailing	1.5	1.5	4.2	0.0	0.0	5.9	3.1	6.3	3.1	3.1	1.9	0.0	0.0	1.9
Other	0.8	1.5	0.8	0.8	0.8	1.7	1.6	4.7	1.6	0.0	1.9	1.9	1.9	3.8
Non-work activity														
School/Daycare/Religious		4.6		10.2				6.3	4.7		9.6		5.8	
Medical/Dental		5.0		2.5				4.7	1.6		3.8		1.9	
Shopping/Errands		**39.5**		18.6				**34.4**	**42.2**		7.7		28.8	
Social/Recreational		14.9		5.1				12.5	14.1		1.9		13.5	
Pick up/drop off		7.7		**24.6**				12.5	4.7		**38.5**		**32.7**	
Buying Meals		16.5		**26.3**				18.8	26.6		28.8		7.7	
Others		11.9		12.7				10.9	6.3		9.6		9.6	

*Notes: Home-based work tours were identified by individuals who used public transit in at least one trip segment. * If multiple modes were used in a trip, only the primary mode was reported.*

Table 2.5 Average duration (minutes) for trip modes and non-works in complex work tours

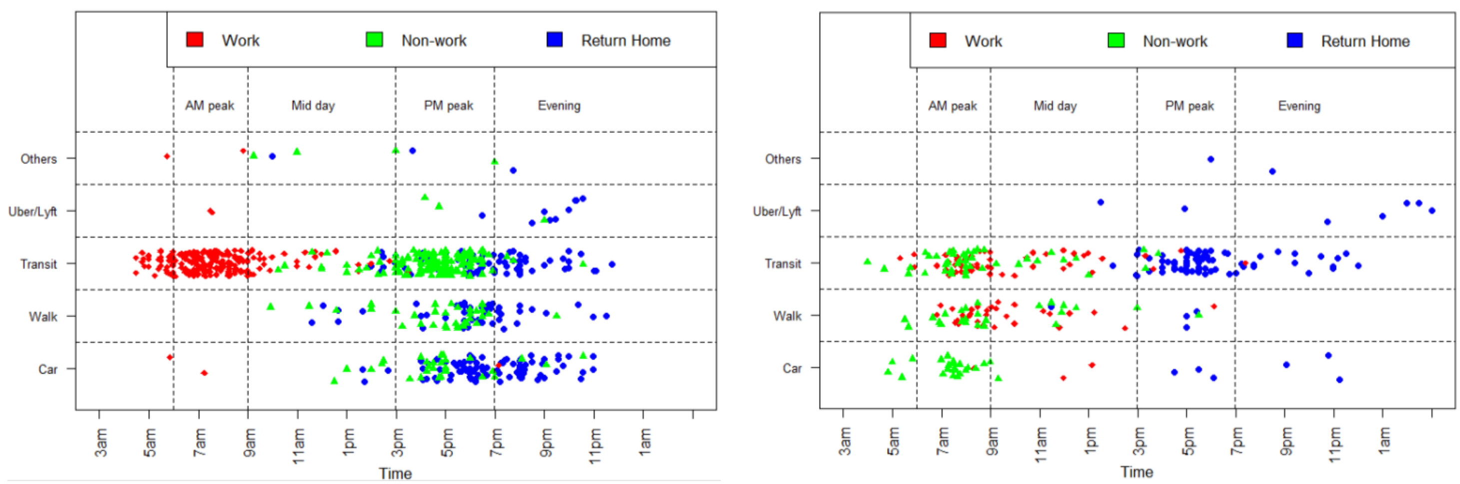
	2a. H-W-N-H			2b. H-N-W-H			2c. H-W-N-N-H				2d. H-N-W-N-H			
Primary mode	N = 262			N= 118			N = 64				N = 52			
	H-W	W-N	N-H	H-N	N-W	W-H	H-W	W-N	N-N	N-H	H-N	N-W	W-N	N-H
Public transit	56.0	54.1	51.4	47.8	58.3	65.2	55.7	59.5	35.5	44.5	56.1	49.1	51.0	47.6
Walk	24.0	14.4	18.7	11.2	10.0	31.5	19.5	11.3	10.8	21.5	9.6	8.7	15.9	15.6
Private vehicle	13.4	39.5	19.4	12.4	12.7	26.7	25.0	33.3	19.2	16.2	14.9	14.5	30.5	26.7
Ride-hailing	24.5	40.0	21.8	0.0	0.0	32.0	24.0	13.5	19.0	12.5	10.0	0.0	0.0	30.0
Other	45.0	35.3	17.5	15.0	7.0	13.5	79.0	21.7	8.0	0.0	40.0	17.0	15.0	30.0
Non-work activity														
School/Daycare/Religious		266.0		156.9				117.0	122.0		53.0		132.3	
Medical/Dental		67.7		125.3				81.7	60.0		67.5		108.0	
Shopping/Errands		37.0		20.5				25.6	47.9		5.0		24.9	
Social/Recreational		161.4		90.8				95.3	168.3		28.0		140.6	
Pick up/drop off		25.6		5.9				13.6	6.7		9.8		12.4	
Buying Meals		59.7		11.1				57.3	72.4		10.1		70.0	
Others		94.5		80.2				174.6	85.5		63.4		78.8	

With the case of two non-work activities before and after work (pattern 2d), it is interesting to note that the purpose of the two non-work activities appear to be negatively correlated: that is, tasks of a certain type performed before work had a lower chance to appear again after work, and vice versa. For example, shopping/errands and social/recreation happen less often before work than after work (7.7 percent versus 28.8 percent for shopping and 1.9 percent versus 13.5 percent for social) whereas buying meals patterns were the converse (28.8 percent and 7.7 percent before and after work, respectively). The only exception to this trend is pick up/drop off, which occurs quite equally in both legs (38.5 percent and 32.7 percent), possibly due to picking up a child from school/daycare after work who had been dropped off before going to work. The most frequent activity performed on the way to work was pick up/drop off. It may be worthwhile to investigate how transit commuters manage to pick up/drop off someone on their way to work or way home since use of transit often involves a change of modes (access/egress modes) and therefore, does not provide as much flexibility and convenience as a private vehicle.

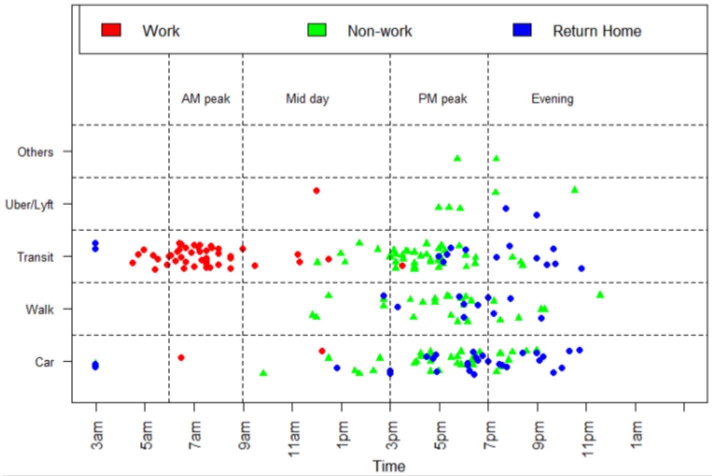
2.5.2.4 Modal distributions

Unlike simple work tours, complex tours combine work with non-work activities in a single tour. Arguably, private vehicles often provide the most flexibility in complex travel, thus, individuals with access to a private vehicle over the duration of a work tour would typically find it flexible and convenient to connect non-work activity demands on a work tour. Since public transit often operates under greater constraints, it can't provide as much flexibility in accommodating non-work activity stops within a work tour. It remains to be answered how travelers who use transit for at least one trip within a work tour manage to connect to non-work activities.

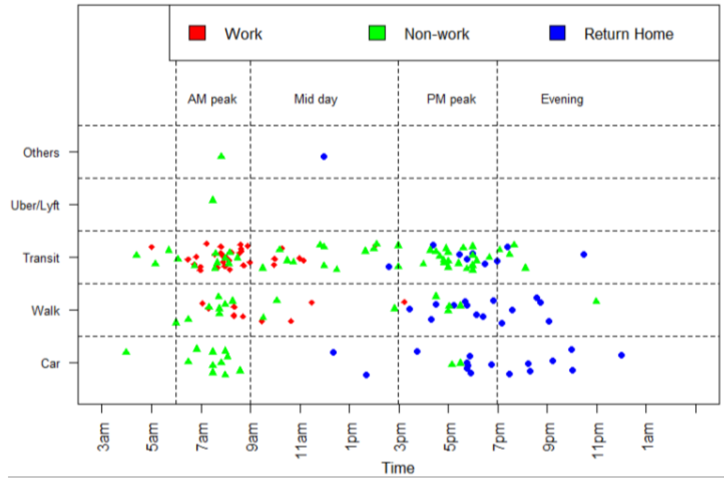
Figure 2.15 Modal distribution by three trip purposes in complex work tours



2a. H-W-N-H (n= 262) **2b. H-N-W-H (n= 118)**



2c. H-W-N-N-H (n= 64)



2d. H-N-W-N-H (n= 52)

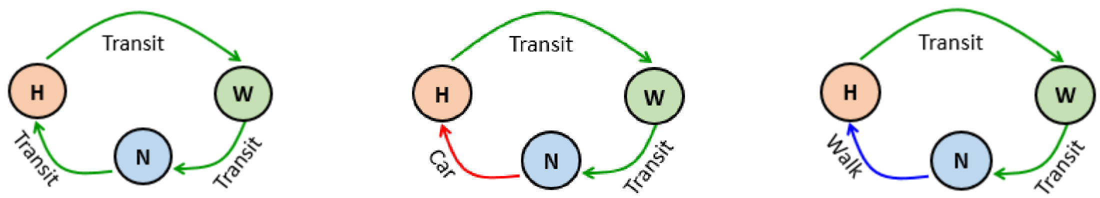
To help understand the modal distribution of trips in complex work tours, we examined the top unshaded section of Table 2.4 and the modal distributions plot in Figure 2.15. Travelers who had non-work activities on their way to work (pattern 2b) had different mode choices returning home than for travelers who performed non-work activities on the way home (patterns 2a, 2c, and 2d). Table 2.4 demonstrates that for pattern 2b transit was dominant for the return home trip, while for the other three patterns in this category, private vehicles dominated on the return home trip. Figure 15 shows that few work tours used ride-hailing services or other modes, regardless of trip purpose, when transit was also used on the tour. Last, in the two tour categories where a non-work activity occurs on the way to work (patterns 2b and 2d), a higher fraction of car and walk trips were recorded during the AM peak period (Table 2.4 and Figure 2.15).

2.5.2.5 Modal sequence by tour

Figure 2.16 shows the three most frequent modal sequences in the identified four patterns of complex tours. We also examined the average travel time for each trip by different modes within a tour from Table 2.5. Combined, the analysis contributes to the understanding of mode usage in activity-travel patterns in terms of activity type and temporal proximity.

The four patterns of complex work tours showed variations in the sequence of mode usage. In pattern 2a, transit was reported as travel mode for all the three trips in the largest fraction of tours (about 20 percent), followed by transit to work and non-work trips and then private vehicle for the return home trip (about 18 percent). In 15 percent of the tours of this pattern type, transit was used for the first two trips and walk was reported for the last trip. This case may be attributed to a choice of a non-work activity in close proximity to home (19 minutes walking time (Table 2.5).

Figure 2.16 Frequent modal sequences in complex work tours

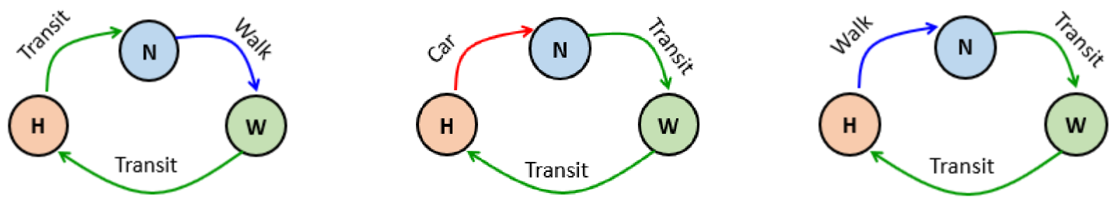


Most frequent sequence (20% tours)

Second-most frequent sequence (18% tours)

Third-most frequent sequence (15% tours)

2a. H-W-N-H (n= 262)

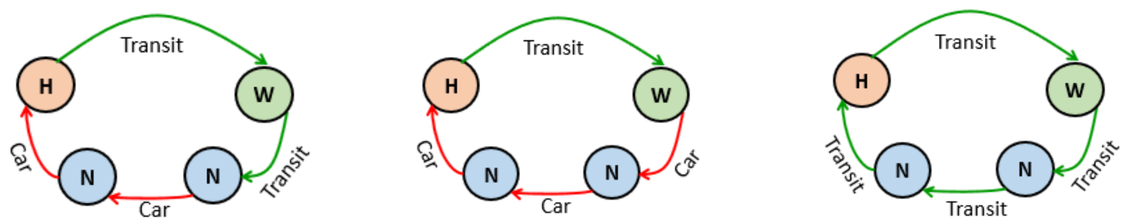


Most frequent sequence (17% tours)

Second-most frequent sequence (16% tours)

Third-most frequent sequence (13% tours)

2b. H-N-W-H (n= 118)

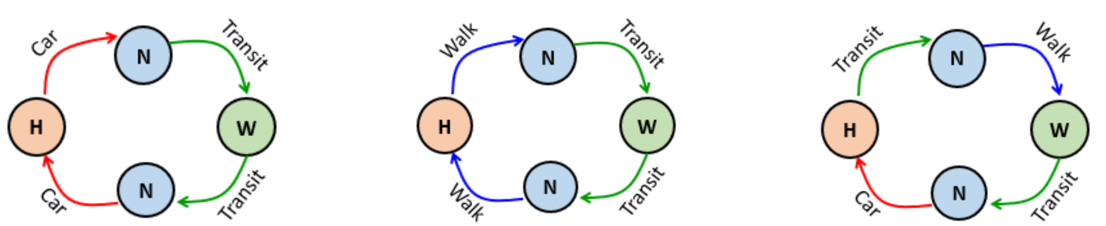


Most frequent sequence (20% tours)

Second-most frequent sequence (15% tours)

Third-most frequent sequence (11% tours)

2c. H-W-N-N-H (n= 64)



Most frequent sequence (13% tours)

Second-most frequent sequence (11% tours)

Third-most frequent sequence (9% tours)

2d. H-N-W-N-H (n= 52)

In pattern 2b, the highest portion of tours (about 17 percent) involved transit use to a non-work activity close to work, followed by on average a 10-minute walk to work (Table 2.5). About the same portion of tours (about 16 percent) used a private vehicle for the first trip to a non-work activity, then took transit to reach the workplace (and also returned home from work via transit). About 13 percent tours involved an 11-minute walk (Table 2.5) to the station, then doing a non-work activity there, and taking transit for both work and return home trips. On these tours, the non-work activities included buying meals (26 percent), pick up/drop off (25 percent), or shopping (19 percent) (Table 2.4). The use of private vehicle for only the first trip in the tour has several potential explanations: (1) travelers were dropped off at a transit station but recorded it as dropping off someone; (2) travelers dropped off someone at their activity location and then drove to the station; (3) travelers drove a vehicle to a station and performed a non-work activity there before taking transit to work, leaving the vehicle at the station (but not having a corresponding trip at the end of the tour); or (4) travelers drove to the station with another traveler. Uncertainty in properly recording complex travel confounds interpretation of the data.

Neither case 1 nor case 4 represent pick up/drop off activities performed by a survey respondent. Case 1 corresponds to being dropped off by someone else and case 4 involves traveling in a private vehicle with someone to change mode at a station. To make further inquiries on these issues, we analyzed those tours where travelers chose modes in the sequence in question (private vehicle (NW) → transit (W) → transit (H)) and record the 'pick up/drop off' in their activity list. In 45 percent of these tours, people dropped off a child at school by using a private vehicle for the first trip. then drove to the station, parked the vehicle, and took transit to work (*case 2*). About 14 percent of the tours represented case 1 suggesting that people misreported the drop off activity in their activity-travel diary. On the other hand, around 21 percent of tours correspond to case 3 while no observed tours reflected case 4.

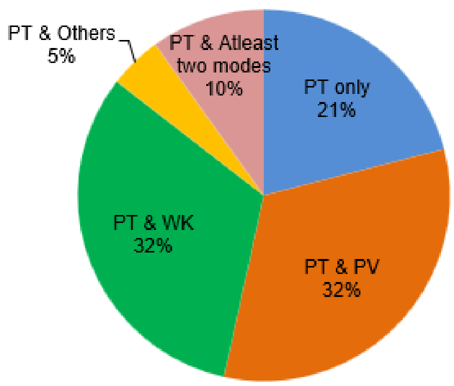
In pattern 2c where travelers made two non-work stops on their way home, 20 percent of tours used transit for the first trip to work. On the return home portion, transit was used to travel to the first non-work location followed by a pick up by someone with a private vehicle to access the second non-work activity (which is located an average of 16 minutes from home (Table2. 5). The final return home trip was with that vehicle. In some of the tours (about 15 percent), transit was used for only the first trip with a later pick up by a household member from the workplace by private vehicle to complete the rest of the tour.

The most frequent modal sequence in pattern 2d was to use a private vehicle for the first and last trips (non-work activities both before and after work) and to use transit for the two middle trips (from non-work to work and the reverse from work to non-work on the way home). The most frequent non-work activity purpose recorded for both directions was drop off/pick up someone (between 33 to 39 percent of tours, Table 2.4). Similar to pattern 2b, this activity sequence invoked some interesting questions. After analyzing the tours where the non-work activity purpose was 'drop off/pick up', we conclude that in most of these tours (about 48 percent) travelers either used private vehicle or walked to drop off children at school/daycare and then drove or walked to a station to take transit to work. After work, they reversed the morning commute (pick up and return home). It appears that some people (about 14 percent of tours) were themselves dropped off but incorrectly reported this as a drop off/pick up activity.

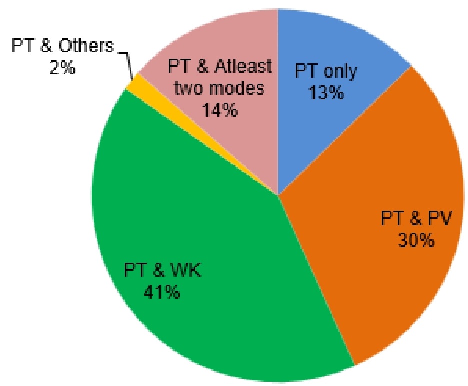
2.5.2.6 Frequency of transit with other modes

From the above analysis, it is evident that transit alone cannot meet all travel demands. While this is not surprising, what is of interest is that most transit commuters use multiple modes to access different activities within a daily work tour. Figure 2.17 depicts the proportion of tours with a combination of travel modes within a complete work tour. Note again that each sampled respondent used transit for at least one trip segment within the work tour, but transit was used in combination with walk, private vehicle, other modes, or any combination of two or more modes.

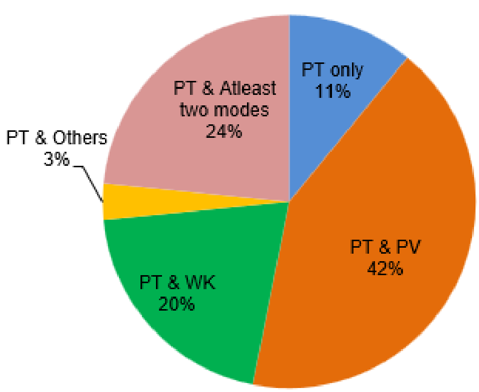
Figure 2.17 Frequency of transit with other modes in complex work tours



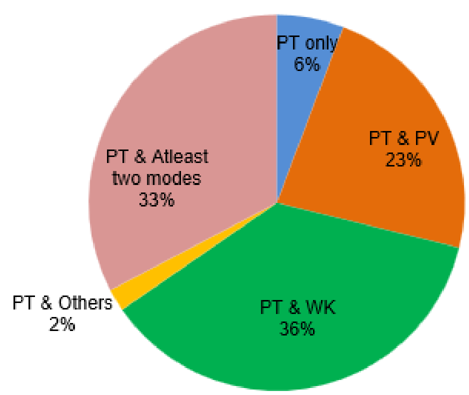
2a. H-W-N-H (n= 262)



2b. H-N-W-H (n= 118)



2c. H-W-N-N-H (n= 64)



2d. H-N-W-N-H (n= 52)

Interestingly, as discussed previously, when travelers simply go to their workplace and then return home (simple tours), the share of transit only tours (PT only) was the largest (83 percent). But when they mixed any non-work activity before or after work, the PT only fraction declined and travelers tended to combine transit with other flexible travel modes, particularly private vehicles, which caused the private vehicle share (PT&PV) to increase (e.g., for *pattern 2c*, the PT only share became 11 percent and the PT&PV share rose to 42 percent).

2.5.3 Complex tour with work-based sub-tour

In this section, the socio-demographic characteristics and travel behavior of travelers who made a work-based sub-tour within a home-based tour (pattern group 3) are discussed. Two dominant work tours (patterns 3a and 3b) were identified representing this tour category.

2.5.3.1 Socio-demographic characteristics

Figure 2.18 provides the socio-demographic characteristics in a spider plot for this group, in reference to simple tours (pattern 1). Pattern group 3 travelers were more likely male, younger or millennials (age 18–38), married (live with spouse or partner), and with higher incomes. Most of their households consisted of two members, both employed. Few travelers in this category had children in their household. Members of this group had at least one household vehicle and the traveler was considered as the primary driver of that vehicle. A much higher fraction of travelers had flexibility in their job arrival time compared to simple or complex work tour makers. In terms of household income, a greater proportion of these travelers belonged to the higher income class than the travelers from the other tour categories.

Figure 2.18 Socio-demographic characteristics of travelers in work-based sub-tour

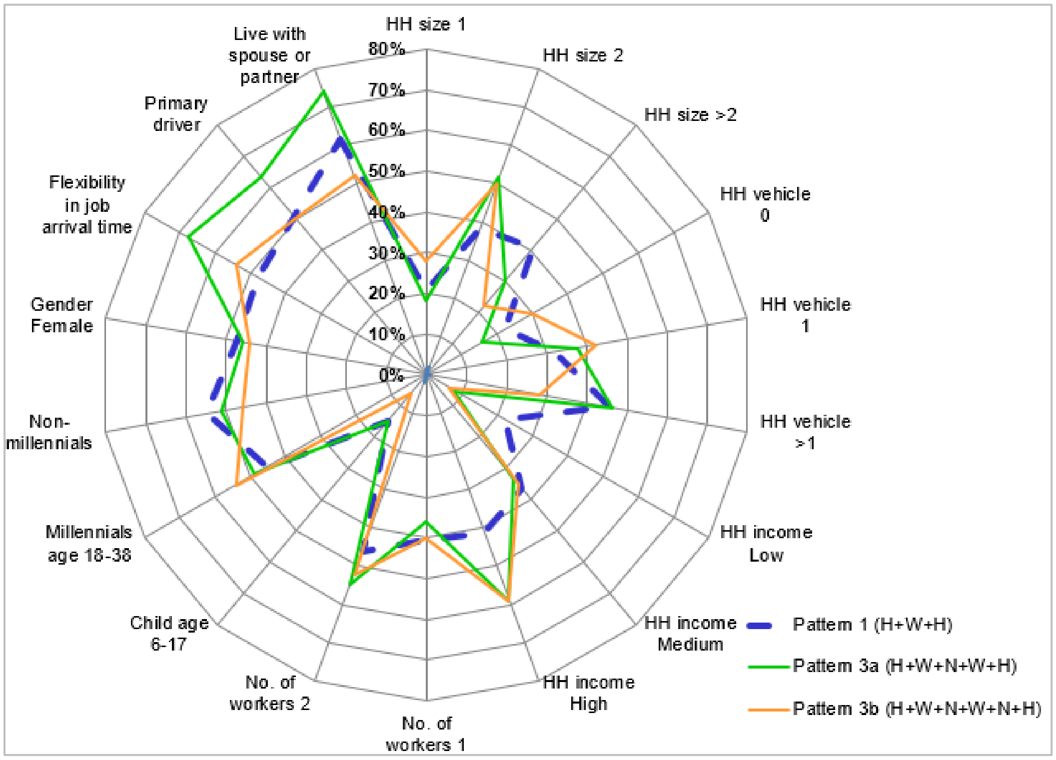


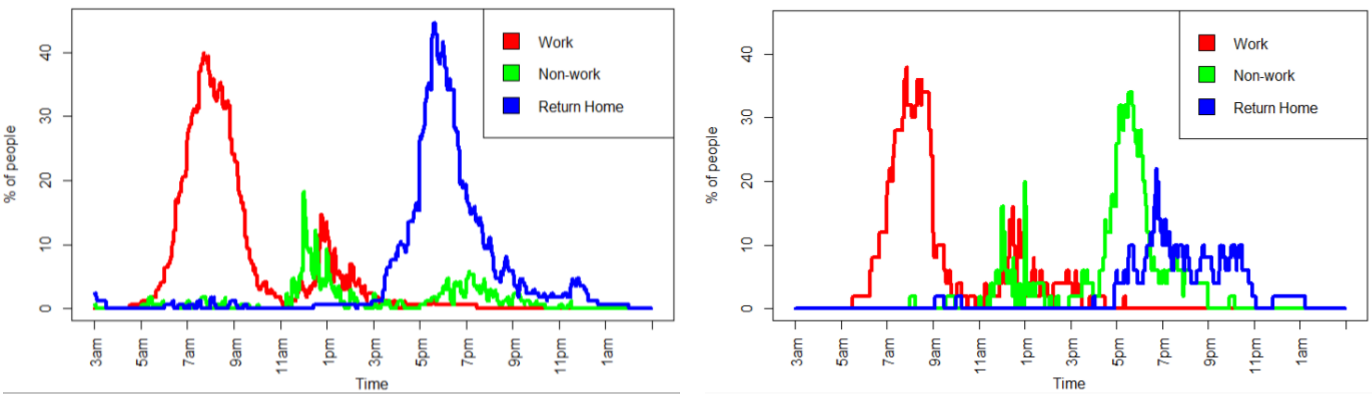
Figure 2.14 also shows that travelers with pattern 3a were more likely to live with a spouse or partner and had higher flexibility in job arrival time than travelers in pattern 3b. The reason for

reporting greater flexibility in job arrival time was perhaps due to the nature of their occupation (78 percent of travelers in pattern 3a reported a professional, managerial or technical occupation compared to 68 percent travelers of pattern 3b).

2.5.3.2 Temporal distribution of trips

Next, the time in motion plot for this tour category was examined (Figure 2.19). Recall that a time in motion plot shows the fraction of travel for a given purpose at various times of a day. Since this category of tours involved making a sub-tour from the workplace, the figure illustrates dual trips to work reflecting the case of accommodating a non-work activity mid-day and then return to work.

Figure 2.19 Time in Motion for three activity purposes in work-based sub-tour



3a. H-W-N-W-H (n= 196) **3b. H-W-N-W-N-H (n= 61)**

2.5.3.3 Non-work activity type and duration

For complex tours with a work-based sub-tour, workers had a mid-day visit to a non-work activity location from their workplace and then returned to the workplace (patterns 3a and 3b, Figure 2.19). Such behavior is explained in Tables 2.6 and 2.7, which suggest that during midday in most of these tours (74 to 77 percent, Table 2.6), workers reported going out for lunch from their workplace, consuming about 23 to 28 minutes, and then returning to work (Table 2.7). In pattern 3b, an additional trip to a non-work location is made, often shopping (about 34 percent of tours, Table 2.6) with an average duration of about 28 minutes (see Table 2.7).

Table2. 6 Percentage of tours for trip modes and non-work activities in work-based sub-tour

	3a. H-W-N-W-H				3b. H-W-N-W-N-H				
	N = 196				N = 61				
	H-W	W-N	N-W	W-H	H-W	W-N	N-W	W-N	N-H
Single mode	98.5	100	99.5	96.4	100	100	100	93.4	96.7
Multiple modes	1.5	0.0	0.5	3.6	0.0	0.0	0.0	6.6	3.3
Primary mode*									
Public transit	93.4	4.1	4.6	86.7	93.4	9.8	9.8	60.7	37.7
Walk	1.5	91.8	92.3	2.0	1.6	86.9	86.9	24.6	21.3
Private vehicle	5.1	2.6	3.1	8.2	3.3	3.3	3.3	13.1	34.4
Ride-hailing	0.0	0.5	0.0	1.0	0.0	0.0	0.0	0.0	6.6
Other	0.0	1.0	0.0	2.0	1.6	0.0	0.0	1.6	0.0
Non-work activity									
School/Daycare/Religious		1.5				1.6		1.6	
Medical/Dental		1.5				3.3		1.6	
Shopping/Errands		9.7				9.8		**34.4**	
Social/Recreational		2.0				1.6		18.0	
Pick up/drop off		0.5				0.0		6.6	
Buying Meals		**77.0**				**73.8**		21.3	
Others		7.7				9.8		16.4	

*Notes: Home-based work tours are identified by individuals who used public transit in at least one trip segment. * If multiple modes were used in a trip, only the primary mode was reported.*

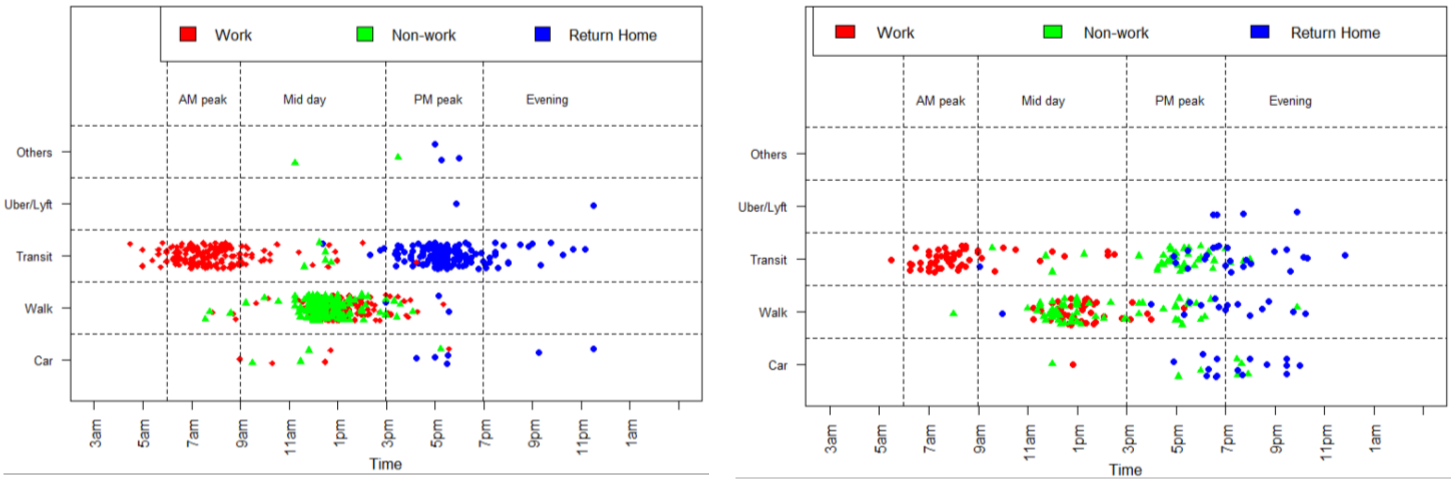
Table 2.7 Average duration for trip modes and non-work activities in work-based sub-tour

Primary mode	3a. H-W-N-W-H				3b. H-W-N-W-N-H				
	N = 196				N = 61				
	H-W	W-N	N-W	W-H	H-W	W-N	N-W	W-N	N-H
Public transit	60.2	22.1	37.1	63.0	51.0	19.7	21.5	48.3	51.3
Walk	25.0	8.2	8.3	31.3	5.0	6.9	7.6	12.3	10.5
Private vehicle	14.8	12.2	66.2	15.6	25.0	12.5	10.0	23.0	16.3
Ride-hailing	0.0	10.0	0.0	24.5	0.0	0.0	0.0	0.0	19.0
Other	0.0	12.5	0.0	43.8	21.0	0.0	0.0	19.0	0.0
Non-work activity									
School/Daycare/Religious		45.7				44.0		75.0	
Medical/Dental		65.0				42.5		50.0	
Shopping/Errands		27.5				36.7		28.0	
Social/Recreational		36.3				35.0		148.0	
Pick up/drop off		10.0				0.0		16.3	
Buying Meals		28.3				22.5		61.6	
Others		44.1				39.3		88.4	

2.5.3.4 Modal distributions

Similar to simple and complex tours, the modal distributions plot was prepared for the work-based sub-tour group and is presented in Figure 2.20. This figure shows that transit was the dominant mode for all trips within the tour except the midday trips to non-work activity locations. In about 87 to 92 percent of these tours, these midday trips were made by walking (see Table 2.6 and Figure 2.20). Such behavior corresponds to conventional lunch hour activity, likely in densely developed areas, such as lunch activity within walking distance of the workplace. In a very few tours, ride-hailing and other modes were used, regardless of trip purpose. In pattern 3b, a considerable fraction of travelers (34 percent), used private vehicles for the return home purpose (see Table 2.6 and Figure 2.20).

Figure 2.20 Modal distribution by three trip purposes in work-based sub-tour

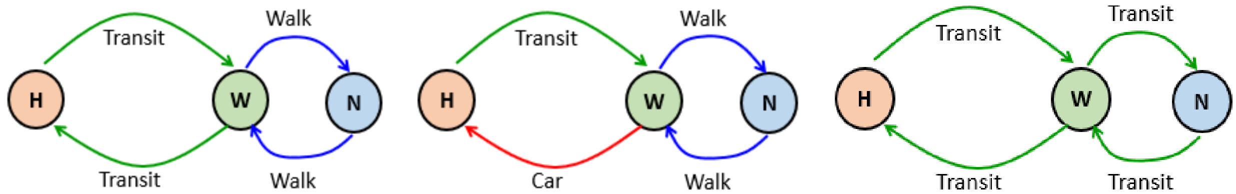


3a. H-W-N-W-H (n= 196) **3b. H-W-N-W-N-H (n= 61)**

2.5.3.5 Modal sequence by tour

Figure 2.21 shows the three most frequent modal sequences of this category of tours. While the modal sequences indicate which trips were chained by which modes, Table 2.7 provides associated trip durations. It was found that the largest fraction of tours (77 percent tours in pattern 3a) involved a long (on average one hour) transit commute to work, with short (on average 8 minutes each way) walking trips during the midday for non-work activities (mostly meals) close to the work location (these are work-based sub-tours). During the evening peak period, the reverse commute via transit was frequent. In pattern 3b, travelers made a 48-minutes transit commute to an additional non-work location (cf. Table 2.7) before returning home.

Figure 2.21 Frequent modal sequences in complex tours with work-based sub-tour

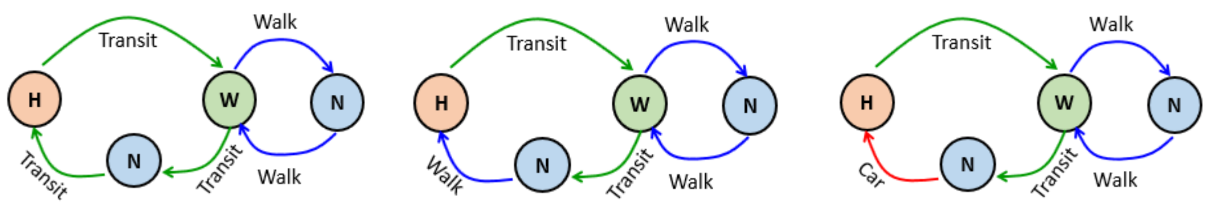


Most frequent sequence (77% tours)

Second-most frequent sequence (3% tours)

Third-most frequent sequence (2% tours)

3a. H-W-N-W-H (n= 196)



Most frequent sequence (18% tours)

Second-most frequent sequence (18% tours)

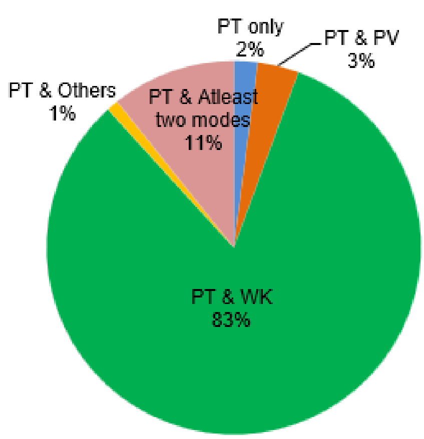
Third-most frequent sequence (14% tours)

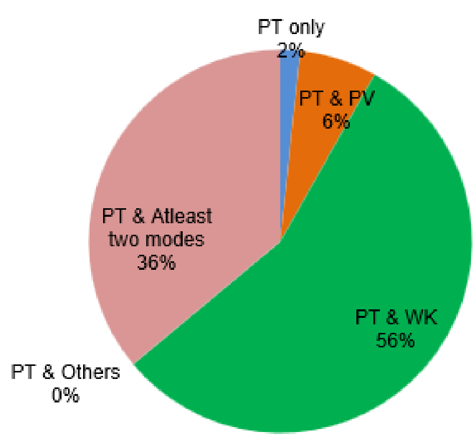
3b. H-W-N-W-N-H (n= 61)

2.5.3.6 Frequency of transit with other modes

While observing the frequency of transit use with other travel modes in this pattern of tours it was found that the share of public transit with walk (PT&WK) was high (cf. Figure 2.22). Note that for pattern 3b transit use in combination with two or more other modes was common (36 percent) because in addition to walk trips at midday, other modes (mostly private vehicles) were used on the return home trip.

Figure 2.22 Frequency of transit with other modes in complex tours with work-based sub-tour





3a. H-W-N-W-H (n= 196) **3b. H-W-N-W-N-H (n= 61)**

2.6 Summary

In this chapter, we analyzed the socio-demographic, trip, and tour characteristics of both transit users and transit commuters by using the 2017 National Household Travel Survey (NHTS) data. Here, the term tour was defined as a sequence of trips and activities that began and ended at home. The primary insights are: (1) transit was utilized for a considerable fraction of work (24 percent) and return home trips (38 percent); (2) about 80 percent of transit work tours consisted of seven dominant patterns whereas the remaining 20 percent of tours demonstrated a total of 106 diverse and more complicated patterns; (3) half of the transit work tours were complex; (4) most simple tours were transit-only tours whereas most complex tours are multi-modal tours; and (5) transit use was more complex than the traditional home to work commute with a diverse set of choices at various stages of activity scheduling. While policies associated with public transit typically focus only on the journey to work, this study considered the complete set of trips starting and ending at home including intermediate non-work activity. This approach can provide insights for land use and transit-related policies to better accommodate the complex travel behavior of commuters who utilize transit.

Chapter 3: Activity-Travel Patterns of Transit Users

Public transit offers lower accessibility and mobility services than private vehicles and thus it is often considered a less attractive mode to many people. To improve the performance of transit and in turn to increase its usage, a better understanding of daily activity-travel patterns of transit users is in order. This chapter analyzes transit-based activity-travel patterns by classifying users using Latent Class Analysis (LCA) . A description of this pattern recognition technique and the model results are discussed below.

3.1 Data and Sample

This study analyzes data from the 2017 National Household Travel Survey (NHTS), a source of information on travel by US residents in all 50 states and the District of Columbia. This survey sponsored by Federal Highway Administration includes data on trips made by all modes of travel (private vehicle, public transportation, pedestrian, biking, etc.) and for all purposes (travel to work, school, recreation, personal/family trips, etc.). The dataset contains the following four data tables:

- Households (socio-economic and location characteristics of surveyed households)
- Persons (demographic characteristics of all household members)
- Trips (over 24-hours by all household members 5 or older and trip-related attributes)
- Vehicles (vehicles used by the responding households)

The NHTS dataset contains 129,696 households consisting of 264,234 persons who took a total of 923,572 trips. For this study, we identified *public transit users* as those individuals who start their first trip from home and ends their last trip at home and used public transit for at least one trip segment[2]. The choice of travel mode was treated as public transit if it was any of the following: public or commute bus, city-to-city bus (greyhound, etc.), Amtrak/commuter rail, and subway/elevated/light rail/streetcar. This generated a sample of 4,994 individuals who made a total of 20,222 trips where almost half of the trips were made by transit (10,011).

3.2 Pattern Recognition Technique: Latent Class Analysis (LCA)

Latent class analysis is a mixture model that hypothesizes that there is an underlying *unobserved* categorical variable that divides a population into mutually exclusive and exhaustive latent classes (Lanza and Rhoades, 2013). Suppose each member of a population (indexed by i) contains J "indicator" variables (indexed by j), each of which can take a value from a set of K_j possible outcomes (all indicators variables are categorical). Let $Y_{ijk} = 1$ if respondent i takes k-th outcome for its j-th categorical variable, and $Y_{ijk} = 0$ otherwise (Y_i denotes the corresponding vector). For a given number of classes, say R, LCA attempts to simultaneously compute: (a) the probability that a respondent falls into a certain class, denoted by p_r, for $r = 1, 2,\ldots R,$ and (b) the class-conditional probability, denoted by $\pi_{jrk,}$ that observation

[2] When a trip involves change of modes, each mode defines a trip segment.

in class r produces the k-th outcome on the j-th variable. The likelihood of observing a certain respondent is therefore given by:

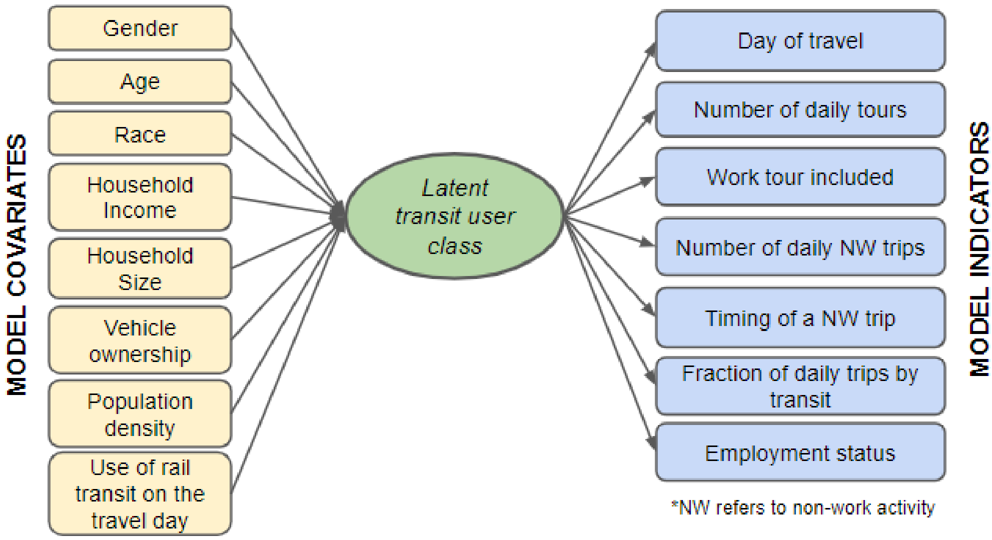
$$f(Y_i|\pi, p) = \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}}$$

The parameters that the LCA model estimates are p_r and π_{jrk}, which are found via maximum log-likelihood estimation (MLE). In a more generalized LCA model, the class probabilities, p_r's, are regressed (by using a logit link function) from a set of observed variables, called "covariates". Hence, the estimation technique finds a set of per class coefficient vectors, β_r (instead of p_r), along with π_{jrk} (more details on this technique can be found in Linzer and Lewis (Linzer and Lewis, 2011).

3.3 LCA Model Indicator Variables and Covariates

LCA requires a set of indicator variables that defines the characteristics of each latent class and a set of covariates that help to predict the probability of an individual belonging to a latent class. Figure 3.1 shows the conceptual latent class model with a set of indicator variables and covariates used in this study. To capture the heterogeneity in activity-travel patterns, we used various *trip* and *tour attributes* of transit users as the indicator variables such as day of travel (weekday or weekend), the number of daily tours (one or more), whether a work tour was made or not, the number of daily non-work trips, the timing of non-work trips, the fraction of daily trips made by transit, and employment status of the transit user. The covariates were selected to understand the class membership profiles that consist of various *socio-demographic* characteristics, such as gender, age, household income, household size, vehicle ownership, use of rail transit on the travel day, and population density (persons per square mile) in the census block group at the home location.

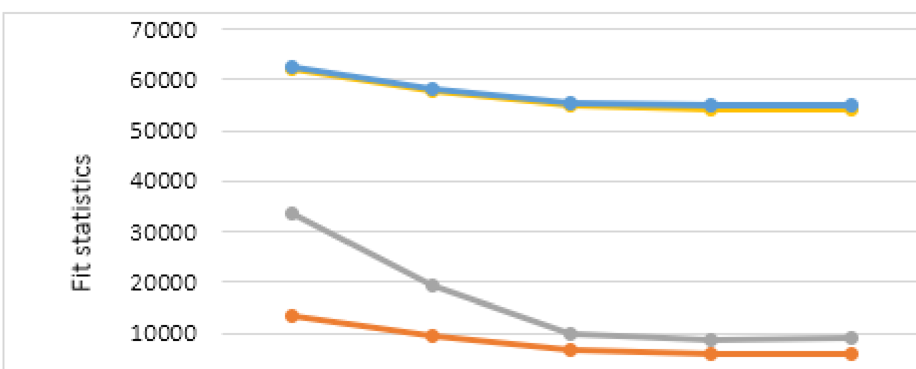
Figure 3.1 Latent class cluster model



3.4 LCA Model Estimation and Fit Statistics

We used poLCA (Polytomous variable Latent Class Analysis) in the statistical software package R to run LCA. R provides model parameters and goodness of fit measures, (chi-square with degrees of freedom and information criteria AIC or BIC). AIC or BIC can be used to compare the relative fit of models with different numbers of latent classes, where a lower value suggests a better model fit. In this study, we varied class sizes from 2 to 6, observed the corresponding fit measures, and empirically assessed the extent of the interpretability of the resulting classes.

Figure 3.2 Model fit statistics for two to six-class models



	2	3	4	5	6
G^2	13566.3	9334.3	6569.5	6055.2	5813.5
Chi-square	33745.5	19246.9	9866.9	8494.5	9137.3
AIC	62325.0	57651.1	54937.0	54094.1	54161.5
BIC	62585.6	58087.7	55549.5	54882.6	55125.9

Figure 3.2 shows the fit statistic values for two to six-class models. With the increase in the number of classes, the values of all fit measures decrease until the class size becomes six. The rate of decrease varies, with a sharp decline after class 2 and then flattening after class 5. Since the five-class model has the lowest AIC and BIC values and classes are easily identifiable and logically interpretable, we accepted the five-class model for our study.

The class-conditional membership probabilities for the indicator variables and class-wise probability-weighted summary statistics for covariate variables are shown in Tables 3.1a and 3.1b, respectively. The class size was determined by assigning an individual to a class for which the probability of that individual belonging to that particular class was the highest (also known as modal assignment). The summary statistics were reported as probability-weighted mean values considering all individuals instead of computing the mean values of the individuals after assigning individual cases to the class with the highest probability. The effects of covariates on class membership are presented in Table 3.2. Each of the identified latent classes corresponds to an underlying group of individuals who are characterized by a particular activity-travel pattern and social-demographics features. Next, we provided a detailed description of (a) who belongs to which among the five identified classes and their trip and tour characteristics, (b) class membership socio-demographic profiles (which factor influenced an individual belonging to a certain class), and (c) the activity-travel patterns of the five classes of transit users.

3.5 The Five Identified Transit User Classes

The first class corresponded to the *simple work tour transit commuters* (22 percent of total users, Table 3.1a) who, as the name suggests, made a single tour (96 percent) for work purposes (97.3 percent) on weekdays (92 percent). This group neither made a nonwork stop in their work tour nor made a separate nonwork tour in a day (100 percent). Most of the members used transit for their work and return home trips (78.9 percent reported using transit for more than 50 percent of daily trips). This group constituted White (63.8 percent), employed males who lived with other household members (81 percent), had high vehicle ownership (79.5 percent), and typically used commuter rail (53.6 percent) for their work trips (c.f. Table 3.1b). The majority of this group (43.4 percent, Table 3.1b) resided in medium-density neighborhoods (2,000 to 10,000 people per square mile).

The second class was identified as the *complex work tour transit commuters* that constitute 22 percent of total users. Similar to class 1, this class also made a single (67.2 percent, Table 3.1a) work tour (97.3 percent) on weekdays but it typically included a non-work stop within the work tour whereas class 1 does not. Several users also made a separate non-work tour to perform a non-work activity (32.8 percent reported making multiple tours). Most of the users made one non-work trip (71.5 percent) per day, usually performed during the midday (10 am – 3 pm) or PM peak period (3 pm – 7 pm). The majority of the members (58.8 percent) depended on transit for making 25 to 50 percent of their daily trips. As per socio-demographic characteristics, these individuals were mostly White (62.9 percent) employed women with high income and high vehicle ownership (75.6 percent) who used commuter rail for work purposes (Table 1b).

Table 3.1a Class-conditional membership probabilities for indicators by class (N = 4,994)

	Class 1	Class 2	Class 3	Class 4	Class 5
	Simple work tour transit commuters (%)	Complex work tour transit commuters (%)	Multimodal complex tour transit users (%)	Simple non-work tour transit users (%)	Complex non-work tour transit users (%)
Class probability	0.22	0.22	0.16	0.19	0.22
Indicator variables					
Day of travel					
Weekday	**0.92**	**0.96**	**0.80**	**0.82**	**0.83**
Weekend	0.08	0.04	0.20	0.18	0.17
Daily tours					
Single tour	**0.96**	**0.67**	0.48	**1.00**	0.44
Multiple tours	0.04	0.33	**0.52**	0.0	**0.56**
Work tour included					
Yes	**0.97**	**0.97**	**0.59**	0.00	0.01
No	0.03	0.03	0.41	**1.00**	**0.99**
Number of daily non-work trips					
Non-work# 0	**1.00**	0.00	0.00	0.00	0.01
Non-work# 1	0.00	**0.72**	0.00	**0.77**	0.00
Non-work# 2	0.00	0.29	0.24	0.23	0.30
Non-work# >2	0.00	0.00	**0.76**	0.00	**0.69**
Timing of a non-work trip					
AM peak (6am – 10am)	0.00	0.19	**0.43**	**0.63**	**0.68**
Midday (10am – 3pm)	0.00	**0.34**	**0.71**	**0.42**	**0.81**
PM peak (3pm – 7pm)	0.00	**0.49**	**0.75**	0.06	**0.53**
Evening (7pm – 6am)	0.00	0.17	**0.43**	0.04	0.16
Fraction of daily trips by transit					
Less than 0.25	0.02	0.13	**0.42**	0.01	0.25
0.25 – 0.5	0.19	**0.59**	**0.50**	0.20	**0.48**
More than 0.5	**0.79**	0.28	0.08	**0.79**	0.27
Employment status					
Employed	**0.98**	**0.98**	**0.96**	0.17	0.10
Not employed	0.03	0.02	0.04	**0.83**	**0.90**

The third identified class was deemed *multimodal complex tour transit users* (this class was smallest with 16 percent of users) who were mostly employed (96.1 percent, Table 1a) and made work tours (59.3 percent) like the first and second classes. The key difference was that class 3 typically made multiple non-work trips (76.3 percent make more than two non-work trips) within a work or non-work tour while the other two classes did not. Despite most of the users being employed in this group, less than two-thirds of them made work tours on the travel day (59.3 percent), which was in contrast to class 1 and class 2 (more than 97 percent did so in these classes).

Table 3.1b Probability-weighted summary statistics for covariates by class (N = 4,994)

	Class 1	Class 2	Class 3	Class 4	Class 5
	Simple work tour transit commuters (%)	Complex work tour transit commuters (%)	Multimodal complex tour transit users (%)	Simple non-work tour transit users (%)	Complex non-work tour transit users (%)
Class size[a]	1095	1127	733	977	1062
Covariates					
Gender of the traveler					
Male	**54.1**	49.5	48.0	46.4	44.3
Female	45.9	**50.5**	**52.0**	**53.6**	**55.7**
Age of the traveler					
Younger group (< 18 years)	0.4	0.5	0.7	**16.7**	**14.2**
Millennials (18 – 38 years)	**40.4**	**42.6**	**47.9**	23.6	17.2
Generation X (38 – 58 years)	**41.1**	**37.8**	**37.2**	21.1	24.2
Older adults (> 58 years)	17.5	17.8	13.5	**36.2**	**43.4**
Race of the traveler					
White	**63.8**	**62.9**	**73.6**	45.7	52.9
Non-white	36.2	37.1	26.4	**54.3**	47.1
Household income					
Low income (less than $35K)	21.1	20.5	18.9	**60.9**	**62.8**
Middle income ($35K – $100K)	35.2	34.4	33.4	21.4	21.6
High income (more than $100K)	**41.4**	**43.4**	**46.8**	13.5	13.1
Household size					
One person	19.0	25.0	29.1	34.0	**40.3**
Two persons	**38.3**	**39.9**	**41.7**	25.0	29.5
more than two persons	**42.7**	**35.0**	29.2	**40.9**	30.2
Household vehicle ownership					
Own at least one vehicle	**79.5**	**75.6**	**71.5**	48.5	43.9
Does not own a vehicle	20.5	24.4	28.5	**51.5**	**56.1**
Used rail on the travel day					
Yes	**53.6**	**55.5**	**59.3**	24.3	23.2
No	46.4	44.5	40.7	**75.7**	**76.8**
Population density (persons per sq. mile) in census block group					
Low density (0 – 2,000)	21.4	15.4	11.7	18.6	17.0
Medium density (2,000 – 10,000)	**43.4**	39.1	38.9	**44.4**	**45.9**
High density (more than 10,000)	35.2	**45.6**	**49.3**	37.0	37.1

Note: [a] Class size is determined by modal assignment. Summary statistics are reported as probability-weighted mean values.

Unlike the other two employed groups, this group made a considerable fraction of multiple tours (52.1 percent compared to 4 percent (class 1) and 32.8 percent (class 2)). The users of this group were multimodal since most of them (more than 90 percent) used transit for at most 50 percent of their trips and depended on other modes for making the rest of the trips. Members of this class were mostly White (73.6 percent) millennials with high income (46.8 percent) and high vehicle ownership (71.5 percent) (c.f. Table 1b). Similar to class 1 and class 2, a higher fraction of this group used commuter rail (59.3 percent). Unlike simple work tour transit users (class 1), a higher fraction of the two complex tour users (class 2 and class 3) lived in high-density residential areas (more than 10,000 people live per sq. mile) (Table 1b).

In contrast to the previous three groups, the last two groups of transit users were not typically employed and consequently did not make work tours. Instead, they made single or multiple tours to perform one or more non-work activities. The fourth group, identified as the *simple non-work tour transit users* (19 percent of total users), primarily made a single tour (100 percent, Table 1a) to participate in only one non-work activity (76.8 percent). This group depended mostly on transit for making both of their trips (79 percent use transit for more than 50 percent of trips) (Table 1a).

Compared to class 4, the final class of transit users (class 5) mostly made multiple tours (55.7 percent) to multiple non-work activities (69.3 percent make more than two, Table 1a). This class was, therefore, called *complex non-work tour transit users*, and comprised 22 percent of total transit users. These two non-work tour classes included a higher fraction of younger (age < 18 years) and older-adult (age > 58 years) groups and a larger proportion of low-income households with low vehicle ownership (about 45 percent in class 4 and 5 compared to about 75 percent in the other three classes) (c.f. Table 1b). Moreover, while a higher proportion of the three employed groups used commuter rail (more than 50 percent), the other two groups mostly used the public bus (more than 75 percent) on the travel day. Among all the classes, class 4 included a larger share of non-Whites whereas class 5 comprised a greater fraction of single-living people. Similar to class 1, the majority of users in both class 4 and class 5 resided in medium-density areas.

3.6 Prediction of Latent Class Membership

The socio-demographic factors (covariates) that influence whether an individual belonged to a particular class are shown in Table 3.2. The covariate coefficients for four classes are displayed relative to the first class (i.e., simple work tour transit commuters). Males were more likely to belong to the simple work tour class (class 1) compared to the other four classes. On the other hand, females were more likely to belong to each of the complex tour classes. This may be because females often have a greater range of activity responsibilities than their male counterparts (McGuckin and Murakami, 1999; Rafiq and McNally, 2020a). Both younger (< 18 years) and older adult groups (> 58 years) were more inclined to be the non-work tour transit users (class 4 and class 5) whereas millennials (18 – 38 years) were more likely to be the multimodal complex tour transit users (class 3).

Household income also affected class membership: transit users with low-income tended to belong to class 4 and class 5, whereas high-income users tended to belong to class 2 and class 3. Likewise, users who did not have a household vehicle or did not use commuter rail were more likely to belong to class 4 and class 5. We found an association between household size and class membership: persons from single-living households tended to belong to class 5, whereas persons from larger households were more likely to belong to class 1. The effects of population density on class membership were limited, with people living in high-density areas more likely to make complex tours, hence tend to belong to class 2 and class 3.

Table 3.2 Prediction of latent class membership (N = 4,994)

Covariates	Complex work tour transit commuters vs. simple work tour commuters	Multimodal complex tour transit users vs. simple work tour commuters	Simple non-work tour transit users vs. simple work tour commuters	Complex non-work tour transit users vs. simple work tour commuters
Gender of traveler: Male	-0.168*	-0.255**	-0.226**	-0.313***
Age of traveler (baseline: Millennials, 18 – 38 yrs.)				
Younger group (less than 18 years)	0.324	0.646	4.542***	4.897***
Generation X (38 – 58 years)	-0.151	-0.300***	-0.249*	0.177
Older adults (more than 58 years)	-0.139	-0.666***	1.212***	1.581***
Household income (baseline: low income, < $35K)				
Middle income ($35K – $100K)	0.084	0.165	-1.210***	-1.097***
High income (>$100K)	0.295**	0.507***	-1.644***	-1.536***
Race of the traveler: white	-0.040	0.490***	-0.267**	0.006
Household size (baseline: single person)				
Two persons	-0.286**	-0.423***	-0.240	-0.167*
More than two persons	-0.525***	-0.880***	0.082	-0.269
Household vehicle: own at least one vehicle (baseline: does not own vehicle)	-0.033	-0.281**	-0.683***	-0.800***
Use of rail transit on the travel day: Yes	-0.033	0.047	-0.655***	-0.755***
Population density (persons per sq. mile) in census block group (baseline: low density, 0 – 2,000)				
Medium density (2,000 – 10,000)	0.198	0.463***	-0.162	-0.036
High density (more than 10,000)	0.507***	0.759***	-0.033	0.085

*, **, and *** indicate statistical significance respectively at 10%, 5%, and 1%.

3.7 Activity-travel Patterns of Identified Classes

This section summarizes the activity-travel patterns of the identified five transit user classes. A graphical representation is utilized for each class that shows the sequence of *all* activities and travel reported in a travel diary day for a *randomly* selected 50 individuals from a given class. Ideally, we would depict the plots for all individuals in the class but space and clarity of display resulted in a selection of 50 patterns yielding the clearest depiction. We generated the same plots for 10 different random samples, each time producing a similar set of plots. We report one of those ten results here. Figure 3.3 shows these results for each class (the x-axis denotes the time of day and the y-axis denotes sampled individuals with their activities and trips). The sequence of activities and travel is shown as segments based on activity and travel duration. The segments are color-coded based on activity purpose and mode use. In Figure 3.3, a summary of the major activity-travel characteristics of each class is also shown by a stacked bar chart beside the activity-travel pattern drawing.

3.7.1 Class 1. Simple work tour transit commuters

The dominance of work (red-colored) segments in all the patterns in Figure 3.3a best illustrates the work focus in this class. The blue segments show transit use, predominantly preceding and following the red segments indicating transit as a commute mode to and from work. The departure time of transit trips during morning and evening hours and the length of red segments demonstrates that this is a 9-to-5 commuter group. In addition to the pattern diagram, the bar chart depicts that this group mostly made a single tour for work purposes and were primarily dependent on transit: 85 percent used only transit, 10 percent used transit in a combination of a private vehicle, and 9 percent combined walk trips with transit. The higher weekly frequency of transit use indicates that this class commuted regularly by transit. The majority of this class were not captive riders[3] but rather were choice riders (66 percent).

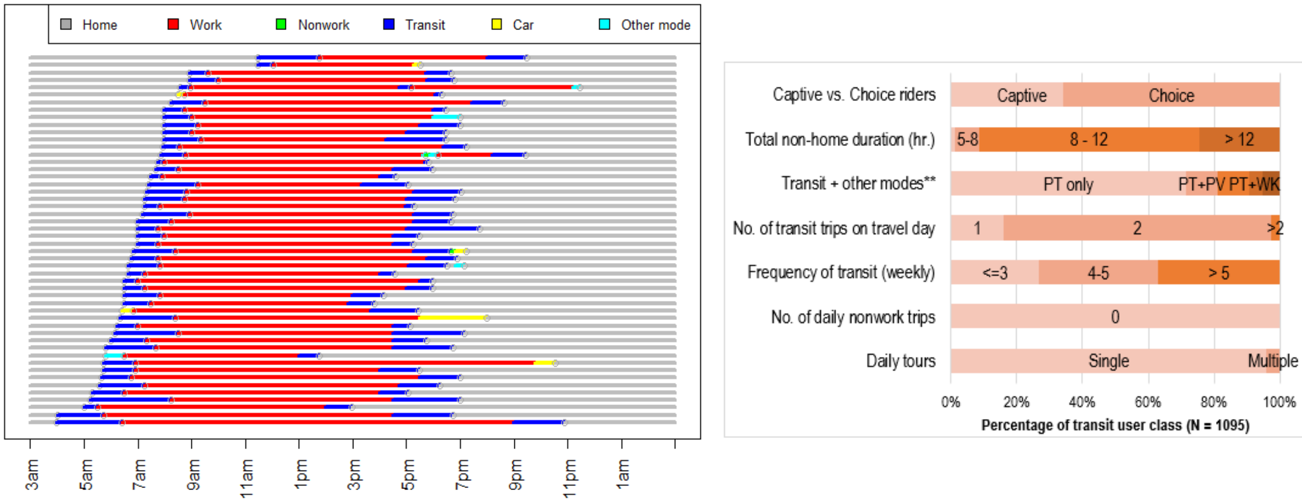
3.7.2 Class 2. Complex work tour transit commuters

In Figure 3.3b, class 2 demonstrates a similar pattern of work (red) and transit (blue) segments like in class 1, which means that class 2 also used transit as a commute mode to and from work. In contrast to class 1, this class also included green segments which depict non-work activities usually performed either during work and/or after work hours (33.5 percent of people had during midday and 49.3 percent during PM peak period non-work activity, Table 3.1a). The after-work non-work activities were made either on the way to home journey or via separate non-work tours. About two-thirds of people in this class made a single tour that typically mixed non-work with work whereas the other third made multiple tours, possibly one for work and another one for non-work. Data revealed that when this group had non-work activity during work hours, they typically went to lunch (spending 28 minutes on average) within walkable distance from their workplace. When the stop was on the way home, the activity tended to be buying goods, groceries, or services, spending about 40 minutes on average.

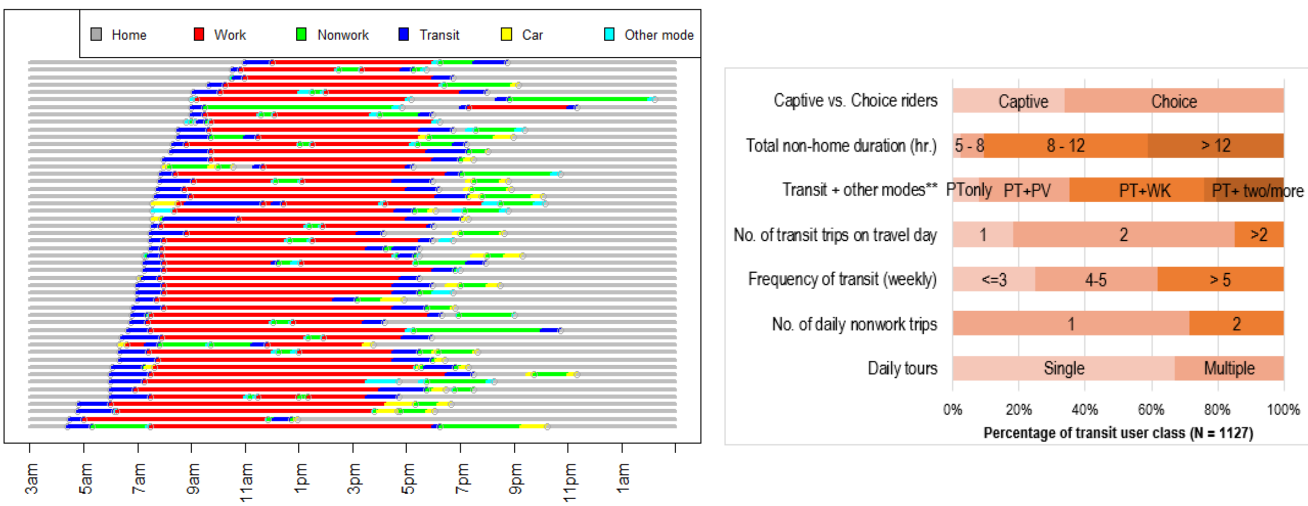
Figure 3.3b also shows that while transit (blue) was predominantly associated with a work activity (red), private vehicles (yellow) and other modes (cyan) along with transit were also used to access non-work activities. For example, in 32 percent of non-work trips transit was reported to be used whereas in 26 percent and 37 percent of trips private vehicles and walk were used to access non-work activities, respectively.

[3] Captive riders refers to those riders who either do not own a vehicle or do not have driving license or give up driving for a medical condition.

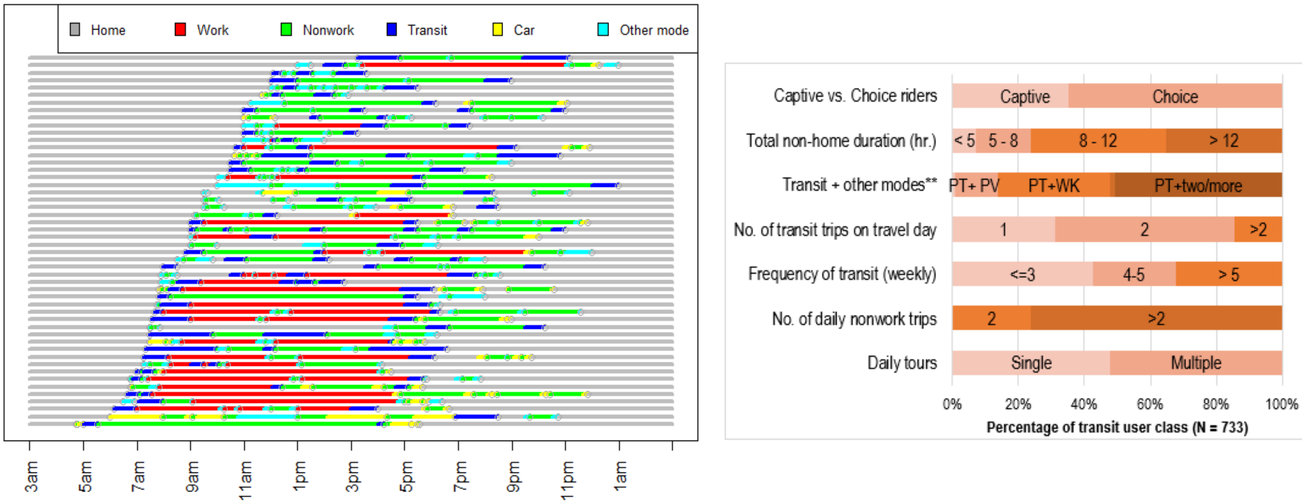
Figure 3.3 Sampled activity patterns and aggregate trip characteristics by transit user classes



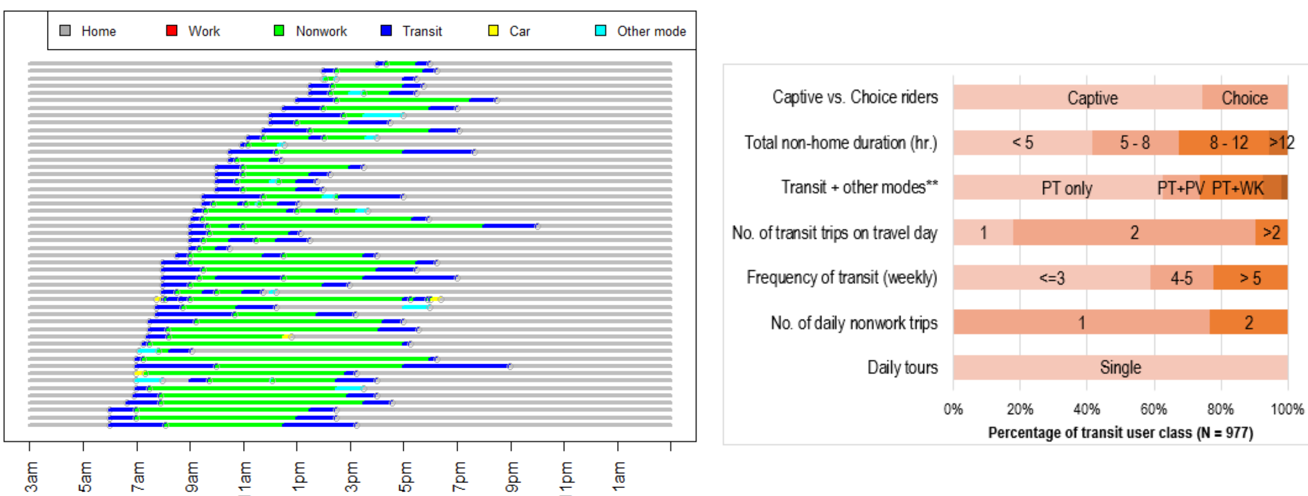
(a) Class 1. Simple work tour transit commuters: 50 random patterns out of 1095 (left) and aggregate trip characteristics of the entire class* (right)



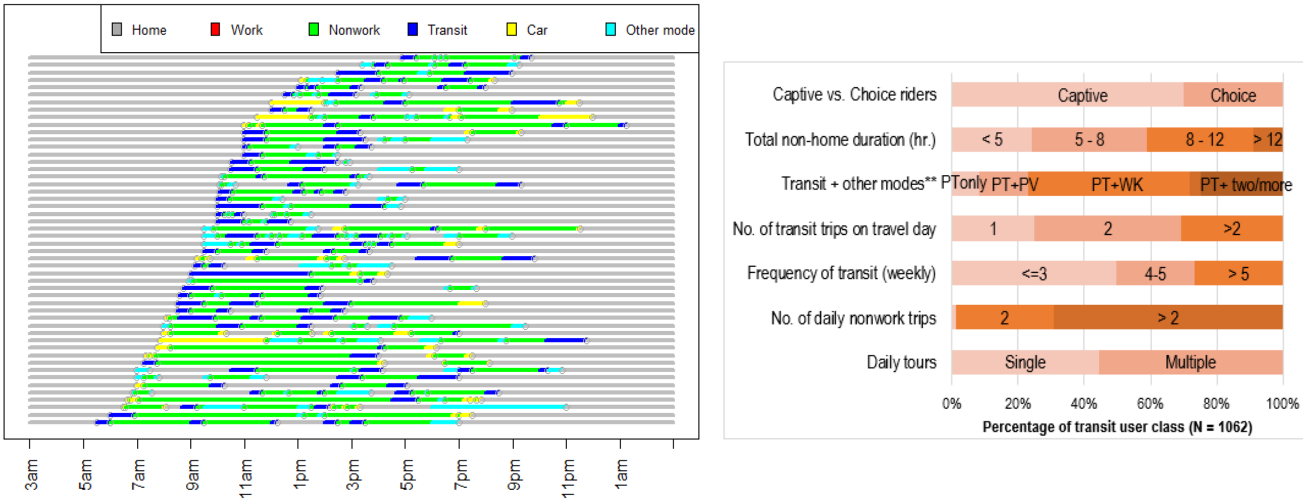
(b) Class 2. Complex work tour transit commuters: 50 random patterns out of 1127 (left) and aggregate trip characteristics of the entire class* (right)



(c) Class 3. Multimodal complex tour transit users: 50 random patterns out of 733 (left) and aggregate trip characteristics of the entire class* (right)



(d) Class 4. Simple non-work tour transit users: 50 random patterns out of 977 (left) and aggregate trip characteristics of the entire class* (right)



(e) Class 5. Complex non-work tour transit users: 50 random patterns out of 1062 (left) and aggregate trip characteristics of the entire class* (right)

* Modes are public transit (PT), private vehicle (PV), walk (WK), and at least two modes (TwoMore).

3.7.3 Class 3. Multimodal complex tour transit users

The transit users who belong to this class demonstrated different trip characteristics from the first two classes (class 1 and class 2), as evidenced in Figure 3.3c. One difference was that not all people in this class made trips to work on the travel day (even though 96 percent of people in this class were employed). A possible reason may be that a higher fraction of class 3 reported weekend trips (20 percent compared to 8 and 4 percent for class 1 and class 2, respectively) or worked from home (12 percent compared to 3 and 4 percent) on the travel day. Another observation was that non-home activities spanned from morning till late evening in this class, which was not visible in other classes (42.8 percent people made trips during the evening compared to 17.4, 3.5, and 16.2 percent in class 2, 4, and, 5 respectively, Table 3.1a). Also, class 3 participated in more non-work activities by making multiple tours and departed late in their first trip made by transit within the first tour than the previous two employed classes. The pattern also revealed that transit users in this class mixed private vehicles (yellow segments) and other modes (cyan segments) with their transit modes (blue segments). This class indeed had a higher fraction of “PT + two/more” group (the travelers who used two and more modes in addition to transit to complete their activities) than other classes (Figure 3.3c bar chart). This is why this class was called a multimodal transit user group.

3.7.4 Class 4. Simple non-work tour transit users

The activity-travel pattern of class 4 is displayed in Figure 3.3d, which shows a similar pattern to class 1 but instead of having work activity (red), class 4 had mostly non-work activity (green). In particular, this class made a single tour to perform one non-work activity and used transit to make the non-work and return home trips (blue segments juxtaposed with green segments). It is observed that the non-work trips mostly occurred during the morning hours (blue segments that precede the green segments spanned 8 am to 12 pm), usually to go to school (19 percent trips), to buy groceries or other goods (35 percent), to visit health care centers (14 percent), or to do discretionary activities (21 percent). As the pattern diagram shows, the total non-home durations for each individual varies. For example, while the majority in this class spent fewer than 5 hours (41 percent), a considerable fraction spent as many as 8 hours (26 percent) or even as many as 12 hours (27 percent) in non-work activity (Figure 3.3d bar chart). This class was neither considered as choice riders nor as frequent transit riders as for other commuter classes. Most of the members used transit constrained by their circumstances (74 percent were captive riders) and used it for at most 3 times a week (60 percent). They rarely used other modes to make non-work trips— only 11 percent and 19 percent of members combined private vehicles and walk with transit, respectively.

3.7.5 Class 5. Complex non-work tour transit users

Members of class 5 made multiple tours to multiple non-work activities as illustrated by a high concentration of small green segments in Figure 3.3e. The green segments spanned from morning through early evening, which was attributed to performing non-work activities during the daytime: 67.5, 81.3, and 52.7 percent users made trips in AM peak, midday, PM peak periods, respectively (Table 3.1a). Non-work trips were usually made for school (8 percent), shopping (40 percent), discretionary activities (28 percent), and medical visits (10 percent). Similar to class 4, the duration of total non-work activities varied considerably among the class members (Figure 3.3e bar chart). The scattered pattern of small blue-colored segments in this class demonstrated a repetitive use of transit for making multiple tours or single tours with multiple trips. Data revealed that compared to other transit user classes, this class made more transit trips with shorter duration (average number of transit trips for class 5 was 2.3 compared to 1.9 for the other classes). The presence of walk (cyan) and private vehicle (yellow) segments denoted corresponding trips which integrated other modes with transit to access multiple non-work activities.

3.8 Activity Patterns of Transportation Disadvantaged Groups

This chapter presented an analysis of the five identified classes of transit users (simple work tour users, complex work tour users, multimodal tour makers, simple non-work tour users, and complex non-work tour users) and their associated activity-travel patterns. Next, we consider the activity-travel pattern of four groups of transit users who are traditionally considered as transit disadvantaged groups. These four groups are people who live in (1) carless households, (2) low-income households, (3) rural areas, and/or who are (4) older adults. Carless households are those which do not own a private vehicle and low-income households are those which earn no more than $35K per year. Rural households reside in an area that is designated as urban or rural as provided in the 2017 NHTS data. Older adults are defined as individuals who are aged 65 and above.

We calculated the distribution of these four transit disadvantaged groups relative to the five identified general transit user classes to determine if these disadvantaged groups tended to be more associated with a particular class and its corresponding activity pattern. Tables 3.3

shows the distribution of the four disadvantaged groups within the five transit user classes. While Table 3.3 shows the distribution as counts, Table 3.4 represents the same data but as percentages. In each table, the first data column provides the class size for the five identified classes, to be split by disadvantaged status. In the second data column,total class members who do not belong to any of the four specified disadvantaged groups is provided while in the third column total class members that belong to at least one of the four specified disadvantaged groups is provided. The remaining columns present the distribution of the four disadvantaged groups. Note that the column sums in Table 3 denote group counts while the corresponding values in Table 3.4 sum to 100 percent. The disadvantaged groups are not mutually exclusive, thus, members in one disadvantaged group can also belong to another group as well.

Table 3.3 Distribution of disadvantaged groups by five identified transit user classes (counts)

Class	Class name	Class size	Class size with no disadvantage	Class size with disadvantage	Carless	Rural	Low-income	Older (>65)
1	Simple work tour users	1095	**685**	410	225	43	230	58
2	Complex work tour users	1127	**681**	446	273	41	228	71
3	Multimodal tour makers	733	418	315	213	26	140	36
4	Simple nonwork tour users	977	240	**737**	501	36	592	211
5	Complex nonwork tour users	1062	211	**851**	597	31	672	289
	Total	4994	2235	2759	1809	177	1862	665

Note: Column 1 represents total class size split by Column 2 (those with no disadvantage) and Column 3 (those with any of the four potential disadvantages. The breakdown of d*isadvantaged groups are not mutually exclusive.*

Table 3.4 Distribution of disadvantaged groups by five identified transit user classes (percentage)

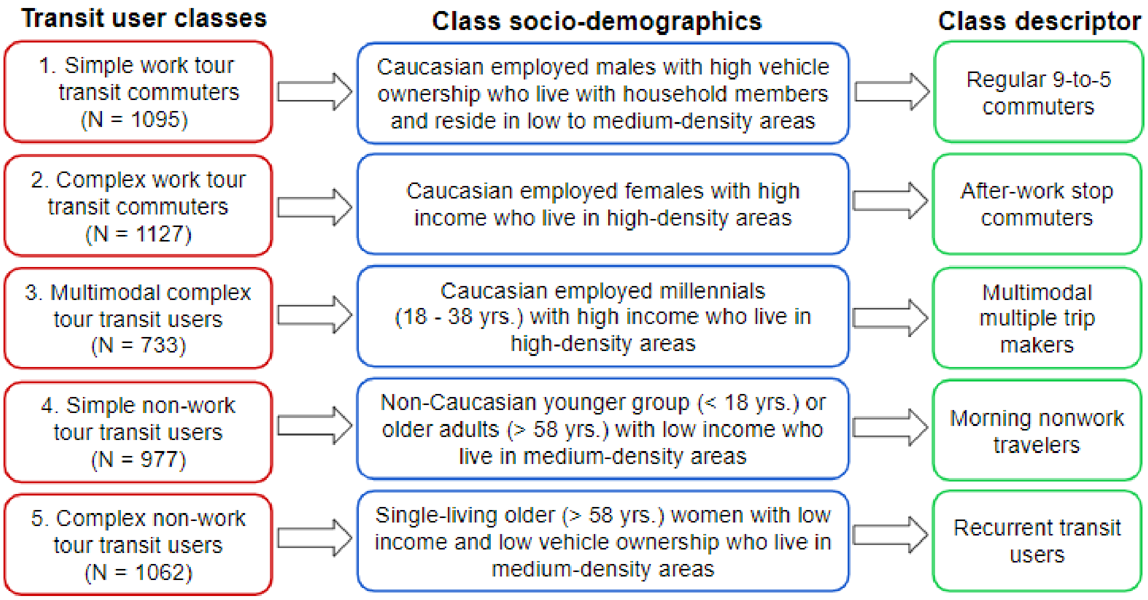
Class	Class name	Class share (%)	Class size with no disadvantage (%)	Class size with disadvantage (%)	Carless (%)	Rural (%)	Low-income (%)	Older (>65) (%)
1	Simple work tour users	**22**	**31**	15	12	**24**	12	9
2	Complex work tour users	**23**	**30**	16	15	**23**	12	11
3	Multimodal tour makers	**15**	19	11	12	**15**	8	5
4	Simple nonwork tour users	**20**	11	**27**	28	**20**	32	32
5	Complex nonwork tour users	**21**	9	**31**	33	**18**	36	43
		100	100	100	100	100	100	100

Among these potentially disadvantaged groups of transit users, carless households and low-income households were more prevalent (see Table 3.3). The percentage distribution of general transit users across the five identified classes closely matched the distribution of users who lived in rural areas but varied over the other disadvantaged groups (Table 3.4). This suggests that transit users living in rural areas might not be different from the general population of transit users relative to the types of activity-travel patterns exhibited (rural residents who did not use transit were not part of the analysis). A larger fraction of carless and low-income households used transit for making non-work tours (Table 3.4). Similarly, older adults used transit primarily for non-work purposes with nearly 43 percent reported making complex non-work tours (Table 3.4). Overall, a larger fraction of transit users (about 60 percent) who did not belong to a disadvantaged group used transit for work purposes, which was the reverse of the pattern for disadvantaged groups where a greater fraction (around 60 percent) primarily used transit for non-work purposes (see Columns 2 and 3 in Tables 3.3 and 3.4).

3.9 Summary

This chapter analyzes the activity-travel patterns and tours of transit users by classifying them into a number of sub-groups via Latent Class Analysis (LCA). Here, the term *pattern* denotes a complete sequence of activities and trips made by a transit user over a full day whereas *tour*, a basic unit of a pattern, refers to a sequence of trips that begins and ends at home and contains single or multiple activities. Based on data from the 2017 NHTS, the LCA model results suggest that the transit users can be divided into five distinct classes where each class has a representative activity-travel pattern (Figure 3.4). Class 1 constitutes employed Caucasian males who make transit-dominant simple work tours. This is a regular 9-to-5 commuter group. Class 2 is composed of white females who commute by transit and typically make after-work non-work activities. Employed white millennials comprise Class 3 and make multimodal complex tours. Class 4 consists of younger non-whites or older adults who make a transit-dominant simple non-work tour. Last, Class 5 members make complex non-work tours with recurrent transit use and comprised single, older women. We observe that disadvantaged groups, such as people from carless households, low-income households, rural areas, and older adults use transit differently than the people who do not belong to the disadvantaged group. Disadvantage groups typically use transit for making non-work and return home trips (non-work activity-travel patterns). These study results can help transit agencies identify potential market groups of transit users with particular socio-demographic characteristics and activity-travel patterns and to take necessary market strategy steps to addressing different groups of users to meet their travel needs and to improve the quality of service provided.

Figure 3.4 Five transit user classes and their socio-demographic properties



Chapter 4: Modeling Work Tour Choice of Transit Users

Public transit is a sustainable mode of transport that can reduce automobile dependency and can provide environmental, economic, and societal benefits. Its widespread adoption and use are arguably dependent on transit's ability to offer effective chaining of trips particularly when utilized on a work commute. Unfortunately, little is known in the context of American travel about the trip chaining behavior of transit commuters. To address this gap, a tour choice model for transit commuters is proposed using Structural Equation Modeling (SEM). The detailed description of the model development and the model results are discussed below.

4.1 Data and Sample

This study analyzes data from the 2017 National Household Travel Survey (NHTS). We identified *public transit commuters* making work tours, that is, those individuals who are at least 18 years old, perform at least one work activity, and used public transit in at least one trip segment. A choice of travel mode is treated as public transit if it is any of the following: public or commute bus, city-to-city bus (greyhound, Mega bus, etc.), subway/elevated/light rail/street car, and Amtrak/commuter rail. This generated a sample of 2,448 individuals. Home-based transit work tours were formed by linking person trip sequences that start and end at home and contained at least one work activity. The result was a total of 2,454 home-based work tours (this includes six individuals who each made two transit work tours on the same travel day). From the total sample, travelers who visited multiple work locations (more than one) but did not mix non-work with work (126 observations) were removed as were those travelers who made two work tours in a day (6 observations). After removing observations with missing information, we obtained a final sample of 2,079 individuals for modeling purposes.

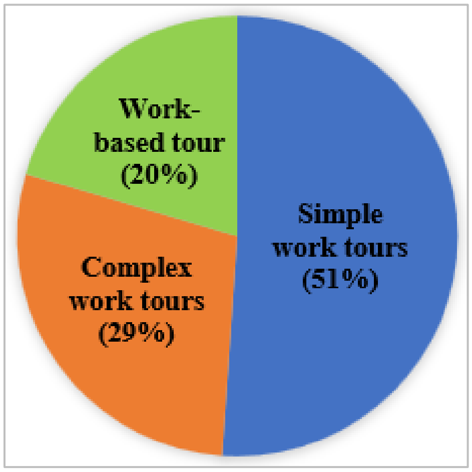
4.1 Types of Work Tours

A home-based work tour is defined as a sequence of trips that starts and ends at home and contains at least one work activity performed at single or multiple destinations. Home-based work tours can be divided into three categories: simple work tours, complex work tours, and complex tour with work-based sub-tours. Detailed definition of these three work tour categories was provided in section 2.5.

The fraction of tours for each of the three categories is provided in Figure 4.2 and shows that both simple work tours and work-nonwork mixed tours overall reflected an almost equal share. Among mixed tours, complex tours represented a higher portion of tours (29 percent) compared to work-based sub-tours (20 percent). The 2017 NHTS data revealed that in simple work tours, transit was typically utilized for both the work-bound and home-bound trips, thus, the share of transit-only tours was the largest for simple tours. In contrast, when travelers mixed non-work activities either before or after work, the transit-only fraction declined, and travelers tended to combine transit with other flexible travel modes (e.g., private vehicles). The share of public transit with walk was the largest in work-based sub-tours, with both walk access/egress and density proximate to the workplace being the likely contributing factors.

Rafiq and McNally (2020b) found that 83 percent of the simple work tours of transit commuters were transit-only tours whereas 92 percent of work-nonwork mixed tours were multimodal tours. When travelers made a non-work stop on the way to work, they often did so for a meal or to drop off a child whereas when they stopped on the way home, the activity tended to be buying goods or services. Users who performed non-work activity during work hours typically went out for lunch within walkable distance from their workplace (Rafiq and McNally, 2020b).

Figure 4.1 Fraction of work tours of NHTS transit commuters (N=2,079)



4.2 Model Specification

Structural equation modeling (SEM) is a comprehensive methodological framework that can simultaneously estimate the causal relationships among a set of observed variables based on a specified model (Kaplan, 2008). Such a structural model can capture the causal influences of the exogenous variables on the endogenous variables (regression effects) and the causal influences of endogenous variables on each other. The structural model also allows provision of error-term covariances (Golob, 2003). The strength of the SEM is that in addition to identifying the direct effect of one variable on another, it also can capture indirect effects through other mediating variables. The summation of direct and indirect effects represents the total effect that provides valuable insights on the interrelationships between variables.

SEM is widely used in travel behavior research as it enables the analysis of complex causal relationships among a set of exogenous and endogenous variables. Golob (2003) outlined a comprehensive review of the application of SEM in various travel behavior research including its use in activity-based travel demand modeling. Several notable studies used SEM to analyze the relationships among socio-demographic characteristics, activity participation, and trip chain behavior (Lu and Pas, 1999; Golob, 2003; Kuppam and Pendyala, 2001; Chen and Akar, 2017; Rafiq and McNally, 2020a). Fujii and Kitamura (2000) applied SEM to identify the association between transportation control measures and commuters' activity-travel patterns. Among recent work, Van Acker and Witlox (2011) used SEM to show how relationships between land use and commuting differ between work-only tours and more complex tours. The relationship of work and non-work trip chaining (tours) with varying mode choice was explored by Islam and Habib (2012) by applying this technique.

This study develops a tour choice model by conceptualizing a causal relationship among a set of socio-demographic characteristics, built environment variables, activity-travel participation, and a particular work tour choice for the public transit commuters by using a SEM *path* model. Path models typically have three types of variables: exogenous variables, endogenous outcome variables, and endogenous mediator variables. An exogenous variable is not causally dependent on any other variables in the model. On the other hand, endogenous variables are determined by the model. An endogenous outcome variable is a dependent variable with respect to other variables used in the model. Whereas, an endogenous mediator variable is independent with respect to some variables and dependent with respect to other variables in the model (Acock, 2013). The SEM path model equations, the conceptualized causal structure, and the list of exogenous and endogenous variables used in our model are described next.

4.2.1 The structural equation path model

Let us denote measured exogenous variables as **X** and measured endogenous variables as **Y**. The equation for the endogenous variables is given by (Kline, 2016):

$$\mathbf{Y} = \boldsymbol{\Gamma}\mathbf{X} + \mathbf{B}\mathbf{Y} + \boldsymbol{\zeta} \tag{1}$$

where **Y** is an (m × 1) column vector of endogenous variable and **X** is an (n × 1) column vector of measured exogenous variables.

The structural parameters are the elements of the matrices are (Golob and McNally, 1997):

$\boldsymbol{\Gamma}$ (m × n) matrix of direct causal (regression) effects from the (n) exogenous variables to the (m) endogenous variables;

B (m × m) matrix of causal links between the m endogenous variables; and

$\boldsymbol{\zeta}$ (m × 1) matrix of m error terms

Equation (1) can be expressed in matrix form as (Kline, 2016):

$$\begin{bmatrix} Y_1 \\ Y_2 \\ \cdots \\ Y_m \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \cdots & \gamma_{1n} \\ \cdots & \cdots & \cdots \\ \gamma_{m1} & \cdots & \gamma_{mn} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ \cdots \\ X_n \end{bmatrix} + \begin{bmatrix} 0 & \cdots & \beta_{1m} \\ \cdots & \cdots & \cdots \\ \beta_{m1} & \cdots & 0 \end{bmatrix} \begin{bmatrix} Y_1 \\ Y_2 \\ \cdots \\ Y_m \end{bmatrix} + \begin{bmatrix} \zeta_1 \\ \zeta_2 \\ \cdots \\ \zeta_m \end{bmatrix} \tag{2}$$

Other parameter matrices include the covariance matrix of the measured exogenous variables **Φ** and the covariance matrix of the error terms **Ψ**, shown in Eq. (3).

$$\mathbf{\Phi} = \begin{bmatrix} \phi_{11} & & & \\ \phi_{21} & \phi_{22} & & \\ \vdots & \vdots & \ddots & \\ \phi_{n1} & \phi_{n2} & \dots & \phi_{nn} \end{bmatrix} \mathbf{\Psi} = \begin{bmatrix} \psi_{11} & & & \\ \psi_{21} & \psi_{22} & & \\ \vdots & \vdots & \ddots & \\ \psi_{m1} & \psi_{m2} & \dots & \psi_{mm} \end{bmatrix} \quad (3)$$

For identification of system (1), **B** must be chosen such that (**I-B**) remains non-singular, where **I** is an identity matrix of dimension *m*. For an identified system, the model implied the total effects of the endogenous variables on each other are given by (Golob and McNally, 1997):

$$\boldsymbol{T_{yy}} = (\boldsymbol{I} - \boldsymbol{B})^{-1} - \boldsymbol{I} \quad (4)$$

The total effects of the exogenous variables on the endogenous variables implied by the system are given by (Golob and McNally, 1997):

$$\boldsymbol{T_{xy}} = (\boldsymbol{I} - \boldsymbol{B})^{-1}\boldsymbol{\Gamma} \quad (5)$$

4.2.2 The exogenous and endogenous variables

Model variables were selected based on relevant prior work and data availability. *Exogenous* variables included household and person-level socio-demographic characteristics. *Household*-level characteristics included the presence of a child (aged 0 to 17 years), the number of adult members (aged 18 years or more), the presence of a spouse or partner (by two categories: employed spouse/partner or single (reference group) and unemployed spouse/partner), the vehicle-driver ratio (number of vehicles divided by the number of licensed drivers), and household income by three categories: low (reference group: less than \$20K), middle income (\$20K to \$60K), and high income (\$60K or more). Several *person*-level characteristics of the travelers, including age, gender, ethnicity, Hispanic status, immigration status, educational attainment, employment type, and flexibility in job arrival time, were considered as important determinants of work tour choice. All person-level variables were represented as dummy variables in the model.

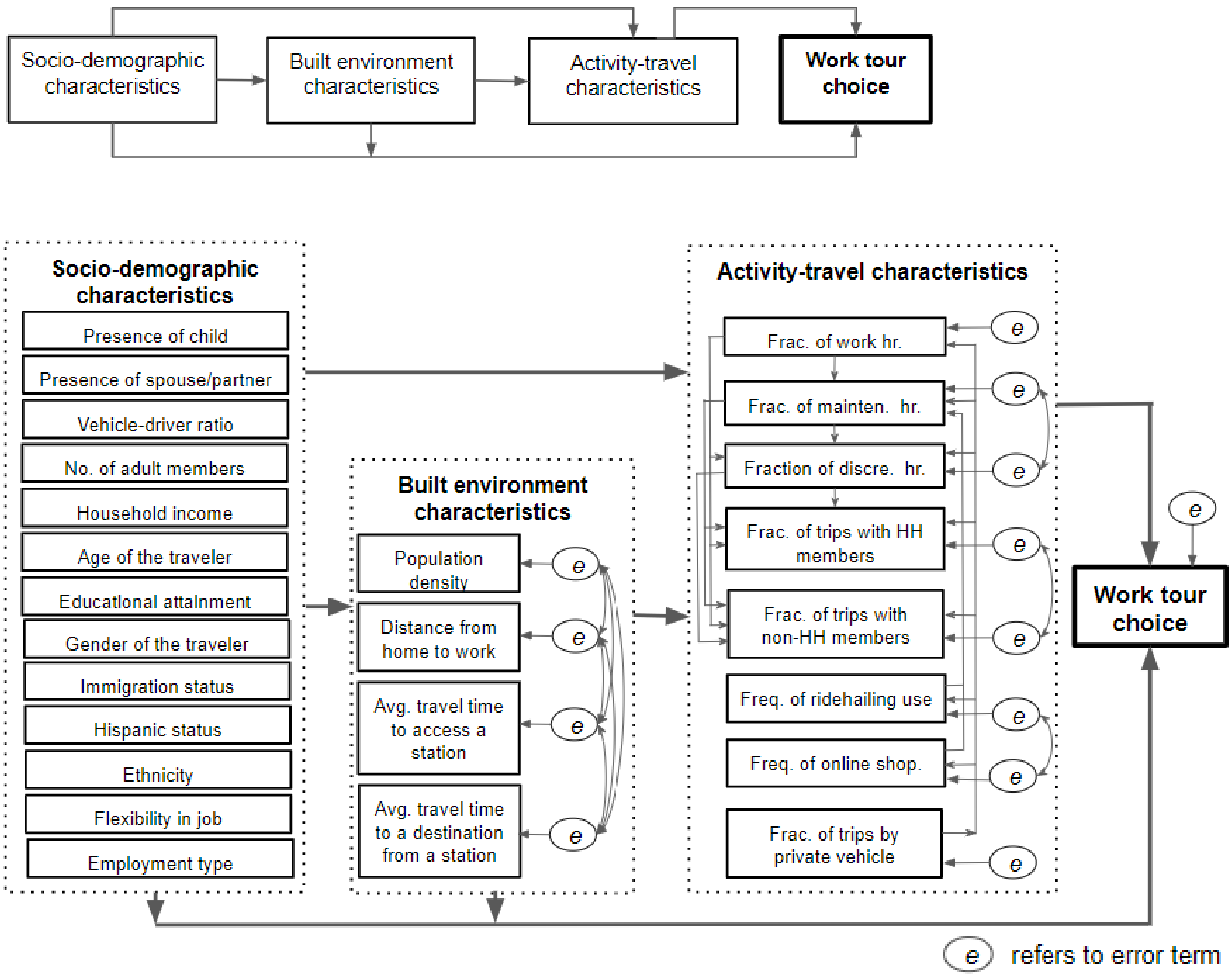
The *endogenous mediator* variables were grouped in two broad categories: the built environment and activity-travel characteristics. The *built environment* variables included population density (persons per square mile) in the census block group of the household's home location, road network distance (miles) between home to the workplace, and proximity of a transit station to either home or work/non-work activity location. This last variable was defined by two variables in the model: one represents the average travel time spent by a traveler to access a transit station from an origin and the other represented the average travel time to access a destination from a station.

The activity-travel characteristics of a traveler were represented by a set of variables. Since trip chaining is often a product of arrangements among household members to gain efficiency in activity-travel engagements (Hensher and Reyes, 2000), we attempted to capture the effects of intra-household interactions on tour behavior. Such interactions are captured by the fraction of hours spent on various out-of-home activity purposes by a household traveler. We considered three such activity purposes — work, maintenance, and discretionary — and thus, three variables in the model. Each of the variables was calculated by dividing the total hours spent on a particular activity purpose by a traveler by the total hours spent on that activity by all the members of the household (including the traveler). Note that maintenance activities included drop off or pick up someone, buying goods, services or other general errands, exercise, health care visit, and religious activities, whereas buying meals, recreational activities, visiting friends and relatives, and volunteer activities are considered as discretionary activities. Other variables that were considered to represent activity-travel characteristics are technology usage behavior, travel party composition, and mode usage behavior. Technology usage behavior was defined by two variables: frequency of ride-hailing app usage and the frequency of online purchases in the last month. Travel party composition was characterized by two variables: the fraction of trips made by a traveler with household members and the same but with non-household members. These two fractions were calculated by dividing the total number of trips made by a traveler with household and non-household members respectively by the total number of trips made by that traveler in a day. The mode usage characteristic of travelers was defined by the fraction of trips where a private vehicle is used within their work tour. The *endogenous outcome* variable defined the choice of a particular work tour by a transit commuter among three work tour types—simple, complex, and complex with work-based sub-tours (a detailed discussion is provided with model estimation).

4.2.3 The conceptual model

The conceptual structure of the SEM can be graphically depicted by a path diagram. An arrow in a diagram indicates the direct effect from one variable to another. The rectangular boxes represent exogenous and endogenous variables. Since an endogenous outcome variable is dependent on all the variables in the model, an arrow is directed *to* it. The conceptual model structure for this study is shown in Figure 4.2. In the model, a set of household and person-level socio-demographic characteristics of travelers and built environment variables were postulated to both directly and indirectly (via activity-travel characteristics) affect their choice of a work tour. Moreover, to capture residential self-selection effects, we posited direct connections from each of the household and person-level characteristics to the built environment variables. Error-term covariances among a similar set of variables, such as the four built environment variables, two technology usage variables, and two travel party composition variables were also added in the model. Last, two error-term covariances were provided between the fractions of household maintenance and household discretionary activities.

Figure 4.2 SEM conceptual structure



4.2.4 Estimation of the model

Based on the conceptual structure (Figure 4.2), *three* SEM path models were estimated with different combinations of a binary outcome variable. These three models facilitated the contrasting of factors between any pair of work tours. For example, in the first model (Model 1 with sample size: 1,654), the binary outcome variable represented the combination of complex and simple work tours. In particular, in this model, we assigned 1 to the outcome variable if a traveler chose a complex tour and 0 otherwise. The purpose of this model is to compare the factors that affect the choice of complex tours with that of simple tours. In model 2 (sample size: 1,487), the outcome variable was 1 if a traveler chose a complex tour with work-based sub-tour and 0 if the choice was for a simple tour. Finally, in model 3 (sample size: 1,017), a contrast between two work-nonwork mixed tours was made. In this model, the outcome variable was 1 if the choice of the work tour was a work-based tour and 0 if it is a complex tour. SEM path models were estimated using the lavaan package in R. We used weighted least square mean and variance adjusted (WLSMV) estimator that works with categorical endogenous variables (one binary outcome variable in each model, which is regressed by a probit function in laavan (R documentation, 2018) and which accounts for non-normally distributed data (Muthen and Kaplan, 1992). The widely used index to evaluate the model fit is χ^2 statistic, which tests whether the observed covariance matrix and the model implied covariance matrix are equal. Smaller χ^2 value with high *p-value* (*p-value* > 0.05) indicates better model fit. Other model fit indices are Root Mean Square Error Approximation (RMSEA), Comparative Fit Index (CFI), Tucker Lewis Index (TLI), and Standardized Root Mean Square Residual (SRMR). The resultant fit statistics for three models and the cut off value for the fit indices are shown in Table 4.1. It is observed that all the model fit indices indicate a satisfactory fit for the three models.

Table 4.1 Model fit indices for the three SEM path models

Model fit indices	Description	Cut-off value	Model-based value		
			Model 1: complex vs. simple (n = 1,654)	Model 2: complex with sub-tour vs. simple (n = 1,487)	Model 3: complex with sub-tour vs. complex (n = 1,017)
Chi-square: χ^2 (df)	A measure of the discrepancy between the observed and model-implied covariance matrices. Smaller value indicates better model fit.	$p > 0.05$	2.27 (5) $p > 0.811$	6.50 (5) $p > 0.260$	7.15 (5) $p > 0.210$
RMSEA	A measure of the amount of error of approximation per model degree of freedom, while controlling for sample size. Smaller value indicates better model fit.	< 0.05	0.000	0.014	0.021
CFI	An assessment of the improvement of the hypothesized model compared to the independence model with unrelated variables. Bigger value indicates better model fit.	> 0.95	1.00	0.99	0.99
TLI	An assessment of the improvement of the hypothesized model compared to the independence model with unrelated variables. Bigger value indicates better model fit.	> 0.95	1.02	0.99	0.97
SRMR	A measure of the mean absolute correlation residual, indicating the overall difference between the observed and predicted correlations. Smaller value indicates better model fit.	< 0.08	0.004	0.006	0.007

Kline (2016), Hu and Bentler (1999), and Van Acker and Witlox (2010)

4.3 Results and Discussion

In this study, three broad categories of interactions (effects) were captured in the SEM model: (a) factors that determined the choice of a particular work tour, (b) factors that influenced residential location variables (residential self-selection), and (c) factors that affected activity-travel characteristics of a traveler. In this section, only the model results of factors that influence the choice of a work tour is discussed. Unstandardized coefficients of *direct* and *total* effects that are statistically significant are discussed. If not otherwise stated, all the effects mentioned in the discussion represent direct effects.

The direct and indirect effects of exogenous and endogenous variables on work tour choice in the three models are shown in Table 4.2. While discussing our model results on transit commuters work tour choice, we contrast our findings with prior studies on generic trip chaining or tour behavior of commuters that did not focus on any particular mode. This will help to understand the similarities and differences of work tour behavior between transit commuters and commuters who travel by any type of mode.

4.3.1. Household and personal characteristics

The choice of a work tour was influenced by a set of household and personal characteristics for a transit commuter. As observed, millennials were less likely to make a non-work stop on either the way to work or to home (complex) but more inclined to pursue non-work activities while at work on a work-based sub-tour (total effect). This is consistent with the notion that younger people might not have childcare activities or household maintenance tasks to consider non-work stops on the way to or from work; instead, they might consider performing non-work activities during the work day, often taking lunch away from work. This finding partially contradicts Castro et al. (2011) who observed that younger individuals are less likely to pursue non-work activity while at work or after work. It is also noticeable that tours performed by males tended to be more elementary than tours performed by females, who frequently link non-work activity on the way to and/or from work. This may be because female workers often have a greater range of activity responsibilities than their male counterparts (Kuppam and Pendyala, 2001; Rafiq and McNally, 2020a). In contrast, males preferred to perform non-work activities during work (typically lunch hour activities outside the workplace). An individual having a college or higher degree was more likely to make any kind of work-nonwork mixed tours. A similar finding was reported in prior work for commuters (Islam and Habib, 2012; Wang, 2015).

Immigration status appeared significant in only model 1 with the implication that immigrants are more likely to make simple tours than native-born people (total effect), which was also reported by Wang (2015). While Hispanic status appeared to be significant in only model 2, ethnicity demonstrated significant impacts on tour choice in all three models, such as Whites being less inclined to consider the way to work or the way home to make non-work stops; instead, they preferred non-work activities during work hours. This finding supports the claim by Wang (2015) that being White is negatively related to complex trip chaining.

Employment characteristics such as fulltime versus part-time and flexibility in job arrival time influenced tour choice. Full-time workers preferred making simple rather than complex tours compared to part-time workers (total effect), but when they make a non-work stop, they preferred to do so during work hours, possibly because work-based periods might appear shorter for part-time workers to make a non-work stop. This finding is consistent with Castro et al. (2011) but different from Islam and Habib (2012). Travelers who have flexibility in work start time appeared to be more inclined to make any kind of work-nonwork mixed tours rather than simple tours. A similar finding was observed in Islam and Habib (2012) and Wang (2015).

The presence of a spouse, children, or other adults significantly affected work tour choice. In particular, a traveler having an unemployed spouse/partner was more likely to make simple tours than complex (Model 1) compared to a traveler who either was single or had an employed spouse/partner. This group of travelers, however, more preferred work-based tours (Model 3) than their counterparts. Similarly, Islam and Habib (2012) also claimed that people having partners were more likely to make simple work tours than single people. On the other hand, individuals having children (aged 0 – 17 years) preferred complex tours (Model 1) over simple tours, perhaps because they might take children to daycare or school or complete shopping for children within a work tour and have fewer opportunities to make separate non-work tours. Between the two types of complex tours (Model 3), they less preferred to perform non-work during work hours (total effect). A similar finding is reported in Hensher and Reyes (2000) for transit commuters and Wang (2015) for commuters irrespective of work mode usage. With the increase in the number of adults in a household, travelers tended to make more simple tours. This was expected since, with other adult members in the household, the responsibilities of essential household maintenance tasks (e.g., taking a child to school/daycare, grocery shopping) can be shared, which consequently reduced the need of a traveler to pursue a non-work activity on a work tour. Similar results appear in Castro et al. (2011), Islam and Habib (2012), and Wang (2015).

Other important household characteristics affecting tour choice were income and vehicle ownership. However, household income did not appear significant in Model 1, which means it did not significantly contribute to determining the likelihood of making complex tours over simple tours, a result consistent with Wang (2015). It yielded significant effects in the other two models. Results showed that both middle- and higher-income travelers were more likely to make work-based tours compared to low-income travelers. Studies that focused on generic trip chain behavior of commuters observed a positive association between household income and complexity of trip chaining (Strathman et al., 1994; Islam and Habib, 2012; Maat and Timmermans, 2006) whereas studies focusing on trip chaining behavior of transit commuters found mixed results. For instance, Hensher and Reyes (2000) observed a positive association but Bernardin Jr et al. (2011) found a negative correlation between household income and the complexity of work tours.

Table 4.2 Direct and total effects of variables on work tour choice in three SEM models

	Model 1: complex vs. simple		Model 2: complex with sub-tour vs. simple		Model 3: complex with sub-tour vs. complex	
	n = 1,654		n = 1,487		n = 1,017	
	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
Household Characteristics						
Presence of child						
B: 1 = if HH has child aged 0-17 years	0.073***	0.077**	0.064**	-0.027	0.015	-0.126***
Presence of spouse/partner						
B:1 = if traveler have unemployed spouse/partner	-0.056**	-0.087**	0.041	-0.027	0.101**	0.056
Vehicle-driver ratio	-0.062**	-0.105***	-0.088***	-0.149***	0.038	-0.033
Number of adult members (aged >=18 years)	0.071**	-0.122***	-0.031	-0.181***	-0.026	-0.044
Household income						
B: 1 = low income (less than $20K) (baseline)						
B: 1 = middle income ($20K to $60K)	-0.034	-0.005	0.123***	0.156***	0.138**	0.134**
B: 1 = high income ($60K or more)	0.004	0.014	0.201***	0.277***	0.220***	0.255***
Personal Characteristics						
Age of the traveler						
B: 1 = Millennials (aged 18 to 38 years)	-0.062**	-0.04	-0.044	0.039	0.012	0.076*
Gender: B: 1 if male	-0.047*	-0.091***	-0.016	-0.014	0.065*	0.065
Educational attainment						
B: 1 = have some college or higher degree	0.032	0.097***	0.141***	0.209***	0.167***	0.135**
Immigration status: B: 1 = if Immigrant	-0.03	-0.057*	0.011	0.01	0.046	0.058
Hispanic status: B: 1 if Hispanic or Latino	-0.018	-0.018	-0.052*	-0.037	0.005	-0.034
Ethnicity: B: 1 = if white	-0.051**	-0.064*	0.079***	0.117***	0.130***	0.173***
Flexibility in job arrival time						
B: 1 if have flexibility	0.043*	0.051	0.095***	0.116***	0.031	0.061
Employment type: B: 1 = if have full-time job	-0.042	-0.084**	0.046	0.027	0.132***	0.114**
Built Environment Characteristics						
Midpoint of population density in census block group of home location (persons per sq. mile)	0.100*	0.104***	0.079**	0.101**	-0.112**	-0.04
Distance from home to workplace (miles) (log)	0.026	0.027	-0.042	-0.124***	-0.119***	-0.170***
Proximity to transit station						
Average travel time to access a station (log)	-0.036	-0.065*	0.000	-0.044	0.066	0.062
Average travel time to a destination from a station (min.) (log)	-0.055**	-0.145***	-0.018	-0.058	0.006	0.072
Activity-travel Characteristics						
Intra-household activity interactions						
Fraction of total household work hours	0.091***	0.078**	-0.056	-0.058	-0.137***	-0.085*
Fraction of total household maintenance hours	0.460***	0.514***	0.284***	2.86	-0.063	-0.068
Fraction of total household discretionary hours	0.467***	0.466***	0.646***	0.669***	0.273***	0.308***

	Model 1: complex vs. simple		Model 2: complex with sub-tour vs. simple		Model 3: complex with sub-tour vs. complex	
	n = 1,654		n = 1,487		n = 1,017	
	Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
Technology usage behavior						
Monthly frequency of ride-hailing app. usage	0.011	-0.006	0.016	0.037	0.001	0.005
Monthly frequency of online purchase	0.028	0.052*	0.007	0.027	-0.003	-0.005
Travel party composition						
Fraction of trips made with household members	0.087***	0.087***	-0.065*	-0.066*	-0.117***	-0.117***
Fraction of trips with non-household members	-0.029	-0.029	0.131***	0.131***	0.163**	0.163***
Mode usage behavior						
Fraction of trips made by private vehicle	0.328***	0.498***	0.178***	0.291***	-0.348***	-0.382***

Note: B = binary variable. *, **, and *** indicate statistical significance at 10%, 5%, and 1% respectively.

Travelers from households with a higher vehicle to driver ratio tended to make simple tours (effect in Model 1 and Model 2), which might be due to having more vehicles per driver in the household which either gave the traveler greater flexibility to make separate non-work tours after returning home or made a vehicle available in the household to be used by other household members to meet household demands. Bernardin Jr et al. (2011) also observed that increasing vehicle ownership corresponds to much simpler transit work tours.

4.3.2 Built environment characteristics

Built environment characteristics affected a person's choice of a work tour. Travelers living in denser areas (higher population density near the residence) were more likely to make any kind of complex tours than simple tours (effect in Model 1 and Model 2). This effect was referred to as an *inducement effect* by Cao et al. (2008) and may reflect that high-density neighborhoods often provide better access to transit service as well as a variety of mixed-use locations that offer opportunities for commuters to generate non-work trips chained to their evening commute to nearby homes or transit stations. A similar effect was also reported in Maat and Timmermans (2006). With increasing distance from home to the workplace, the consideration of a work-based period for engaging in non-work activities declined (effect in Model 2 and Model 3), possibly because a longer commute might exhaust commuters and discourage them from making additional trips from and to the workplace during midday. Proximity to a transit station appeared significant in only Model 1. It shows that with the increase of average travel time to or from transit stations, travelers were less inclined to make complex tours.

4.3.3 Activity-travel characteristics

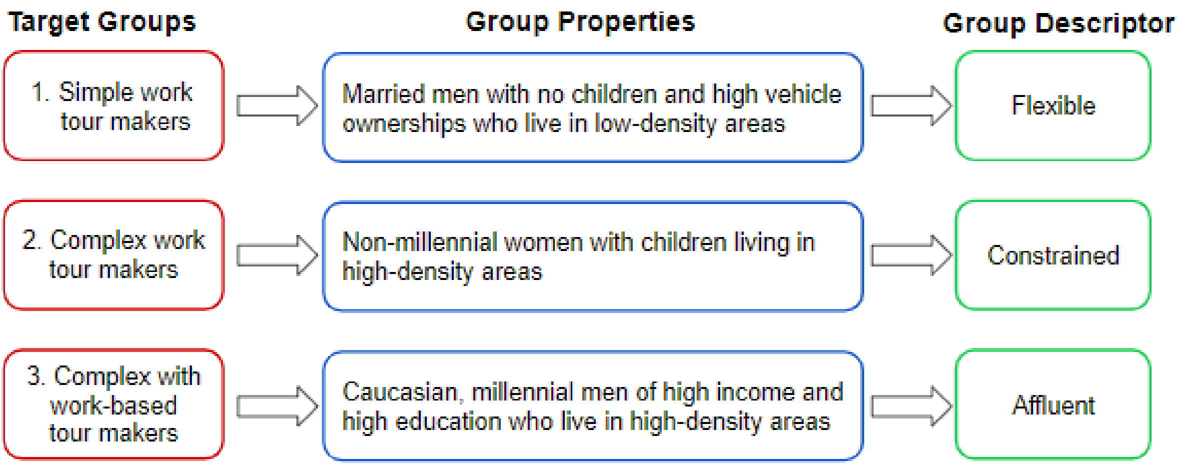
With the increase of the fraction of total household work hours made by a traveler, the tendency of making complex tours increased (Model 1) but the tendency of making complex with work sub-tours decreased (Model 3). On the other hand, the increase in the fraction of total maintenance hours contributes more to making any kind of work-nonwork mixed tours than simple work tours. Similarly, the increase of the fraction of total household discretionary hours is linked to making work-nonwork mixed tours more than simple tours. Discretionary stops were more likely to be made during work hours (lunch activity during midday) (Model 3). Technology usage such as the monthly frequency of ride-hailing app usage or online shopping did not significantly affect the choice of work tours.

Interestingly, who accompanies a traveler on a trip affected tour choice. For example, when individuals made trips with household members, their chance of making complex tours increased, and the tendency of making work-based sub-tours declined. Conversely, with the increase of the fraction of trips made with non-household members, the chance of making work-based sub-tours increased. Non-work stops made on the way to work or on way to home were more likely to be made with household members to drop off/pick up someone from the same household. On the other hand, a non-work stop made during work hours was more likely to be made with co-workers (non-household members) for lunch. The use of a private vehicle in the work tour was a discernable effect in all three models. With the increase of the fraction of trips made by private vehicle, the tendency to make any kind of work-nonwork mixed tours increased (model 1 and model 2). While comparing the two work-nonwork mixed tours, the increasing fraction of private vehicle usage decreased the chance of making work-based sub-tours compared to complex tours (model 3).

4.4 Summary

This chapter presented a tour choice model that was developed to define public transit commuters based on the complexity of their work tours and to assess the impact of causal interactions among household and person-level socio-demographic characteristics, built environment variables, and activity-travel engagement on the likelihood that a transit commuter would choose a particular type of work tour. We used an SEM *path* model to conceptualize a causal relationship among a set of socio-demographic characteristics, built environment variables, activity-travel characteristics, and a particular work tour choice. Based on the 2017 NHTS data, the model results suggested that neighborhood density, flexibility in work schedule, household activity interactions, travel party composition, and availability of private vehicles on work tours were important determinants of work tour choice for transit commuters. The results also defined the three groups of work tour makers. In particular, simple work tour makers were typically married men with no children and with high vehicle ownership living in low-density areas. Second, complex work tour makers were non-millennial women with children who lived in high-density areas. Finally, millennial, White men of high income and high education living in denser areas tended to make complex tours with work-based sub-tours. By examining these group properties, it appears that in terms of flexibility in household activity scheduling due to household structure and resources, simple tour makers were the most flexible group whereas complex tour makers were the most constrained. And, work-based tour makers appeared to be a more affluent group compared to the other two groups. The summary of the characterizations of these three groups is shown in Figure 4.3.

Figure 4.3 Three target groups of transit commuters and their properties



Chapter 5: Findings, Policy Implications, and Limitations

This research analyzes the activity-travel patterns and tour formation of transit users by using the 2017 National Household Travel Survey data. A tour was defined as a sequence of trips that begins and ends at home and contains at least one out-of-home activity whereas a pattern was defined as the complete sequence of activities and trips made over a full 24-hour day. In this study, we addressed three major research objectives. The findings and associated policy implications of each of the objectives are discussed below.

Objective 1. Identify the Complex Travel Behavior of Transit Users

The first objective was to examine *how* and *when* public transit commuters incorporated non-work activities in their work tours using basic descriptive analyses (Chapter 2). We identified dominant patterns of work tours made by transit commuters and analyzed these tours using a set of activity-travel analytics. The primary insights and key implications of this objective are:

Finding 1.1 *About 80 percent of work tours consist of seven dominant patterns whereas the other 20 percent of tours demonstrate a total of 106 diverse and more complicated patterns*.

To the best of our knowledge, this study was the first to analyze the full work tours with transit use in various positions in the pattern sequence so this simple categorization and analysis of tour types is considered as a contribution to theory and practice. We identify seven dominant work tour patterns that represent 80 percent of the tours and these patterns were placed in three broad tour categories: simple work tours, complex work tours with four sub-categories, and complex tours with work-based sub-tour with two sub-categories. Based on the choice of a particular work tour, this study identified potential transit commuters. For example, tours performed by males tended to be more elementary than tours performed by females, who frequently linked non-work activity either on the way to work or on the way to home, a result consistent with the greater range of activity responsibilities for female workers (Strathman *et al.*, 1994; McGuckin and Murakami, 1999; Kuppam and Pendyala, 2001; Rafiq and McNally, 2020). On the other hand, higher-income people did not frequently make non-work stops on their way to work or to home (complex tours); instead, they tend to do so within the work hour (making work-based tours). Similarly, younger or millennial travelers mostly made work-based tours whereas non-millennials preferred to make simple or complex work tours.

This information can help transit operators in identifying potential markets and their associated demand for transit over the course of a day. This information can help to better evaluate current transit services and to implement market strategies (e.g., fare structures) that can meet the complex travel needs of potential users, which can lead to increased transit use. For example, people who make multiple transit stops within a work tour could be provided discounted fare options such as a day pass or free transfers which might encourage commuters to use transit to reach non-work activity locations along with their workplace.

Finding 1.2 *In terms of complexity, half of the transit work tours are complex*.

Previous studies showed that the majority of workers who use transit in their work tours are more likely to make home-based simple tours (McGuckin *et al*., 2005). We observed that an equal share of simple and complex work tours existed for transit commuters. Among all the work tours where transit is utilized, 49 percent represented elementary or simple tours. On the other hand, 51 percent of tours involved complex tours (complex with and without sub-tours) where commuters were observed to chain either multiple work activities but no non-work activity (5 percent) or to mix non-work activities with work on the way to, during work, or on the way to home (46 percent). Among these work-nonwork mixed tours, most of the travelers (60 percent) made at least one non-work stop on the way to home travel. About 35 percent and 41 percent of travelers did so on the way to work journey and during the work day respectively. While making a non-work stop on the way to work, travelers most often dropped off a child or bought a meal. When a non-work stop was made on the way to home, the activity tended to be buying goods or services. If travelers performed a non-work activity during work, they typically went out for lunch within walkable distance from their workplace.

It is apparent that public transit work tours were notably complex, which was partially supported by Bernardin Jr et al. (2011) who showed that contrary to common belief, public transit tours were at least as complex as tours by other modes. Our tour-based analysis contributed to understanding the interrelationships and consistencies among the choice of activities, timing, locations (proximity), duration, and modes used for the full set of trips comprising a complex tour. Since public transit offers less flexibility of travel in accommodating complex travel needs than private vehicles, the findings of our study provide an empirical justification for evaluating policies that can better address the complex travel demands of transit commuters.

Finding 1.3 *In terms of mode use, most simple work tours are transit-only tours whereas most complex tours are multimodal tours*.

The study results suggested that when non-work activities are linked with work, transit commuters tended to be multimodal, mixing other travel modes with transit. We found that simple work tours were predominantly transit-only tours (83 percent) whereas most work-nonwork mixed tours were multimodal tours (92 percent). It was observed that when travelers perform non-work activities with work, they tended to combine private vehicles or walk with transit. For example, a common non-work activity performed on the way to work is dropping off children at school. It would not be convenient for a commuter to chain such non-work activity locations (e.g., schools) with home or the workplace by using transit since connecting these facilities (home - non-work - workplace - home) involves multiple transfers, waiting time, and access/egress issues. To provide a convenient modal linkage, transit stations should be designed to consider parking facilities and other activity services.

Finding 1.4 *Transit use is more complex than the traditional home to work commute with a diverse set of choices at various stages of activity scheduling*.

While policies associated with public transit typically have focused only on the journey to work, this study reconsidered the complete set of trips, starting and ending at home and including intermediate non-work activity. Although transit use was observed to be predominantly associated with the work-end of the tour (a direct connection to or from work) due to better transit services in employment centers, it was also noticed to be utilized at the non-work end of the tours. Identifying the range of transit use as part of complex travel provides a foundation to formulate better land use and transit-related policies to satisfy demands for complex tours with a larger share for transit. For example, providing mixed land use developments at employment centers might help transit commuters to access non-work activity centers in off-peak periods within walking distance of workplaces. In addition, non-work activity centers can be located near transit stations or residences. When locating such facilities, planners could consider providing multiple activity centers (e.g., shopping/grocery, restaurants) at a single location. This might reduce the number of transfers for commuters when they utilize public transit to access non-work activities and facilitate performing multiple activity purposes at a single location within a work tour.

The empirical analyses in this study can lead to a better understanding of how transit commuters link non-work activities with work, which can improve our knowledge of linkages between activity and mobility. Identification of such information is crucial and at the same time challenging for better understanding the development of tour- or activity-based demand models (Wang, 2015). TRB (2007) indicated that the analytical complexity and prohibitive data demands of tour- or activity-based models enable only a small number of US transportation agencies to apply them. We analyze tour behavior of transit commuters applying an activity-based approach, but this does not directly represent an activity-based (or tour-based) *forecasting* model. However, the insights of this study can be utilized to develop better tour-based models that reflect the complexity of transit use within tours.

Objective 2. Identify Classes of Transit Users based on Complex Travel Behavior

The second objective was to apply a comprehensive classification approach, Latent Class Analysis (LCA), to study the activity-travel behavior of transit users. The goal was to identify latent classes of transit users based on the heterogeneity in activity-travel patterns and then associate those classes with particular socio-demographic characteristics of transit users.

Finding 2.1 *Transit users can be classified into five distinct classes, each with a representative activity-travel pattern*.

The LCA model results suggested that transit users can be divided into five distinct classes where each class had a representative activity-travel pattern. Class 1 constitutes employed White males who made transit-dominant simple work tours. This is a regular 9-to-5 commuter group. Class 2 was composed of White females who commute by transit and typically make after-work non-work activities. Employed White millennials comprised Class 3 and made multimodal complex tours. Class 4 consisted of younger non-White and older adults who made a transit-dominant simple non-work tour. Last, Class 5 members made complex non-work tours with recurrent transit use and were composed of single, older women.

These research findings can help transit agencies identify potential market groups of transit users with particular socio-demographic characteristics and activity-travel patterns and to propose market strategies that address these different groups of users to meet their specific travel needs and thus to improve the quality of service provided. For example, frequent transit services and on-time strict schedules need to be ensured and monthly transit pass option can be offered particularly to those who regularly use it for commute purposes (Class 1 and Class 2). While making after-work non-work activities, a substantial portion of Class 2 members use private vehicles for non-work or return-home trips as transit use is not generally conducive to do so. To provide a convenient modal linkage for this class, transit stations should be designed to consider parking facilities and other activity services.

Since individuals belonging to Class 3 made multiple trips to non-work activity locations and usually mixed other modes in addition to transit, providing multiple activity centers (e.g., shopping/grocery, restaurants) at a single location might be of benefit. This might reduce the number of transfers required for transit use and might facilitate completing multiple activity purposes at a single location. On the contrary, since Class 4 and Class 5 comprised a large portion of older adults, special attention needs to be given to design better and convenient transit services for them addressing their mobility and accessibility needs. Finally, Class 5 transit users made frequent use of transit (multiple times in a single day) so discounted fare options (e.g., a transit day pass or free transfers) could be offered so that they can make multiple transit-stops in connecting non-work activities.

Finding 2.2 *Transportation disadvantaged groups have different activity-travel patterns than those who do not belong to any of the specified disadvantaged groups*.

Among the potentially disadvantaged groups of transit users, carless households and low-income households were more prevalent. A larger fraction of carless and low-income households used transit for making non-work tours. Similarly, older adults used transit primarily for non-work purposes with nearly 43 percent reported making complex non-work tours. In general, a larger fraction of transit users (about 60 percent) who did not belong to a disadvantaged group used transit for work purposes, which was the reverse of the pattern for overall disadvantaged groups where a greater fraction (around 60 percent) primarily used transit for non-work purposes.

Although transit services have typically better accommodated peak commuters (work trips) rather than off-peak travelers, our results suggest that transit authorities should consider improvements in off-peak hour services to address the travel needs of these transit-dependent groups, particularly for those who have limited modal alternatives or who depend primarily on transit due to age, income, or disability. Improving public transit facilities by addressing transit-dependent groups can increase their mobility and may indirectly encourage greater transit us in the general population. Identifying travel needs and barriers to personal mobility for transit disadvantaged groups is important in establishing effective policies to reduce travel inequities.

Objective 3. Develop a Tour Choice Model for Transit Users

The third and final objective was to develop a tour choice model to characterize public transit commuters (who) based on the complexity of work tours and to assess the impacts of various demographic, location, and activity-travel factors on the likelihood that a transit commuter would choose a particular type of work tour (*why*) by applying Structural Equation Modeling.

Finding 3.1 *Structural models suggest that neighborhood density, flexibility of work schedules, household activity interactions, travel party composition, and availability of private vehicles in work tours were important determinants of work tour choice for transit commuters.*

Finding 3.2 *Structural model results provided the demographic characterization of three groups of work tour makers (simple, complex, and complex with work-based sub-tours).*

The Structural Equation Model results not only identified the important determinants of transit tour choice but also enabled the characterization of three groups of work tour makers. In particular, simple work tour makers were most often married men with no children, with high vehicle ownership, and living in low-density areas. Complex work tour makers tended to be single, non-millennial women with children who live in high-density areas. The third group of millennial White men with higher income and higher education living in denser areas commonly made complex tours with work-based sub-tours.

The characterization of the above three transit commuter groups can help transit providers to identify potential market groups and to formulate market strategies targeting the respective groups. For example, discounted fare options (e.g., a transit day pass or free transfers) could be offered or parking facilities at transit stations could be made available to the group of commuters who have more constraints in household activity participation or who need to make multiple transit stops in connecting non-work with work within a work tour.

Unlike previous studies on commuter tour behavior, this study captures the nature of work tour complexity in greater detail by dividing complex tours into distinct categories. More specifically, transit commuters who made a non-work stop before and/or after the work activity (creating peak-hour demand) are separated from those who had stops during work hours (off-peak hour demand). If short-term travel demand management policies to reduce peak-hour traffic (such as alternative work schedules) were to be proposed, the results of this study can provides guidance to identify those commuters who might be best served by such policies.

This study contributes to better understanding the circumstances of transit commuters that facilitate chaining non-work activities before, during, or after work. For instance, our study results indicated that flexibility in job arrival time and access to of a private vehicle in a work tour increased the chance of making mixed work-nonwork tours. Fixed transit schedules and fixed work start times often pose greater constraints on transit commuters in making a non-work stop, particularly in the morning peak period. Without access to a private vehicle, it becomes more difficult for a transit commuter to drop off children at school during the morning period or to do grocery shopping during the evening period. To address such temporal and spatial constraints of transit commuters, modal integration is needed between transit and other flexible travel modes. In this regard, an integrated transportation system could be developed as a part of a commute program in collaboration of transit operators, on-demand ride-hailing service operators (e.g. Uber/Lyft), and employers, where transit will act as the central part of the system with pooled on-demand ride-hailing as a complementary mode to provide first and/or last mile solutions and to facilitate connecting non-work trips with work, for which transit does not currently offer a convenient linkage. In addition to providing better accessibility and lower travel time to the travelers, the integration of pooled on-demand services with traditional public transit could lead to a reduction in the number of vehicles, carbon emissions, and congestion (Martinez and Viegas, 2017).

The tour choice models developed in this study can be used by transit agencies or other planning organizations to forecast the nature of work tours made by a commuter with particular socio-demographic, location, and activity-travel characteristics, which can aid in predicting the number of stops made within a work tour for each commuter and then to schedule a work tour in an activity-based travel demand forecasting model.

Limitations

There remain some limitations in this study. Detailed location data was not available in NHTS, thus it was not possible to capture the impacts on tour complexity of land use distributions or accessibility indicators near home, workplace, or transit stations. Since NHTS data contains single-day diary data, the activity-travel behavior reported is specific to the survey date. We recognize the limitations of not only NHTS but of all surveys and how well they can represent underlying behavior. However, research suggests that single-day travel surveys of appropriate sample size can capture the underlying distribution of behaviors. While the day in question may not be typical of an individual respondent, the sum total over all respondents captures the overall distribution of travel behaviors.

Regarding latent classes, the size of the categories identified are based on the NHTS sample and do not necessarily reflect the size of these classes in any particular location or time period. We do believe that these categories reflect dominant behaviors in the population as a whole and that the size of each category reflects the relative size in the population, given spatial variation. In other words, the categories identified are not broadly inclusive of all behaviors, but we believe they do reflect the broad range of dominant transit behaviors. Last, surveys from different areas might produce additional (or fewer) user categories and different category sizes but we believe that our derived LCA classes are both intuitive and statistically robust.

References

APTA. (2017). Who rides public transport: passenger demographics and travel. American Public Transit Association.

Abenoza, R. F., Cats, O., & Susilo, Y. O. (2017). Travel satisfaction with public transport: Determinants, user classes, regional disparities and their evolution. Transportation Research Part A: Policy and Practice, 95, 64-84.

Acock, A. C. (2013). Discovering structural equation modeling using Stata. Stata Press books.

Alemi, F., Circella, G., Handy, S., and Mokhtarian, P. (2018). What influences travelers to use Uber? Exploring the factors affecting the adoption of on-demand ride services in California. Travel Behaviour and Society, 13, pp. 88-104.

Alemi, F., Circella, G., Mokhtarian, P., and Handy, S. (2018). Exploring the latent constructs behind the use of ridehailing in California. Journal of choice modelling, 29, 47-62.

Allahviranloo, M., Regue, R., & Recker, W. (2017). Modeling the activity profiles of a population. Transportmetrica B: Transport Dynamics, 5(4), 426-449.

Alonso-González, M. J., Hoogendoorn-Lanser, S., van Oort, N., Cats, O., and Hoogendoorn, S. (2020). Drivers and barriers in adopting Mobility as a Service (MaaS)–A latent class cluster analysis of attitudes. Transportation Research Part A: Policy and Practice, 132, 378-401.

Arentze, T. A., & Timmermans, H. J. (2009). A need-based model of multi-day, multi-person activity generation. Transportation Research Part B: Methodological, 43(2), 251-265.

Arentze, T., Hofman, F., van Mourik, H., & Timmermans, H. (2000). ALBATROSS: multiagent, rule-based model of activity pattern decisions. Transportation Research Record, 1706(1), 136-144.

Axhausen, K. W., and Gärling, T. (1992). Activity-based approaches to travel analysis: conceptual frameworks, models, and research problems. Transport reviews, 12(4), 323-341.

Beckman, J. D., and Goulias, K. G. (2018). Immigration, residential location, car ownership, and commuting behavior: a multivariate latent class analysis from California. Transportation, 35(5), 655-671.

Bernardin Jr, V. L., Swenson, A., Jiang, Z., & Grovak, M. (2011). Income effects and other new findings on complexity of transit tours. Transportation Research Record, 2217(1), 38-45.

Bhaskar, A., and Chung, E. (2014). Passenger segmentation using smart card data. IEEE Transactions on intelligent transportation systems, 16(3), 1537-1548.

Bhat, C and Koppelman, F (2003). Activity Based Modeling of Travel Demand. In Hall, R. (ed.) Handbook of Transportation Science. Kluwer.

Bhat, C. (1999). An analysis of evening commute stop-making behavior using repeated choice observations from a multi-day survey. Transportation Research Part B: Methodological, 33(7), 495-510.

Bhat, C. R., Astroza, S., Bhat, A. C., & Nagel, K. (2016). Incorporating a multiple discrete-continuous outcome in the generalized heterogeneous data model: Application to residential self-selection effects analysis in an activity time-use behavior model. Transportation Research Part B: Methodological, 91, 52-76.

Bhat, C. R., Guo, J. Y., Srinivasan, S., & Sivakumar, A. (2004). Comprehensive econometric microsimulator for daily activity-travel patterns. Transportation Research Record, 1894(1), 57-66.

Bhat, C. R., and Singh, S. K. (2000). A comprehensive daily activity-travel generation model system for workers. Transportation Research Part A: Policy and Practice, 34(1), 1-22.

Bianco, M. and Lawson, C. (1996). Trip chaining, childcare and personal safety: critical issues in women’s travel behavior. In Proceedings from the second national conference on women’s travel issues. Washington DC

Cao, X., Mokhtarian, P. L., and Handy, S. L. (2008). Differentiating the influence of accessibility, attitudes, and demographics on stop participation and frequency during the evening commute. Environment and Planning B: Planning and Design, 35(3), 431-442.

Castro, M., Eluru, N., Bhat, C., and Pendyala, R.(2011). Joint model of participation in nonwork activities and time-of-day choice set formation for workers. Transp. Res. Rec. 2254, 140-150.

Chen, Y. J. and Akar, G. (2017). Using trip chaining and joint travel as mediating variables to explore the relationships among travel behavior, socio-demographics, and urban form. Journal of Transport and Land Use, 10(1), 573-588.

Cheng, L., Chen, X., Yang, S., Wu, J., and Yang, M. (2019). Structural equation models to analyze activity participation, trip generation, and mode choice of low-income commuters. Transportation Letters, 11(6), 341-349.

Chu, K. K. A., and Chapleau, R. (2010). Augmenting transit trip characterization and travel behavior comprehension: Multiday location-stamped smart card transactions.Transportation research record, 2183(1), 9-40.

Chung, J. H., Kim, S., Lee, Y. K., and Choi, Y. S. (2004). Multilevel structural equation model for activity participation and travel behavior: Data from the Puget sound transportation panel. Transportation Research Record: Journal of the Transportation Research Board, (1898), 52-60.

Currie, G., & Delbosc, A. (2011). Exploring the trip chaining behaviour of public transport users in Melbourne. Transport Policy, 18(1), 204-210.

Davis, A. W., McBride, E. C., and Goulias, K. G. (2018). A latent class pattern recognition and data quality assessment of non-commute long-distance travel in California. Transportation research record, 2672(42), 71-80.

De Oña, R., López, G., de los Rios, F. J. D., & de Oña, J. (2014). Cluster analysis for diminishing heterogeneous opinions of service quality public transport passengers. Procedia-Social and Behavioral Sciences, 162, 459-466.

Pacific Southwest Region UTC
University Transportation Center

Diana, M., & Mokhtarian, P. L. (2009). Grouping travelers on the basis of their different car and transit levels of use. Transportation, 36(4), 455-467.

Doherty, S. T., Miller, E. J., Axhausen, K. W., and Garling, T. (2002). A conceptual model of the weekly household activity/travel scheduling process. In: E. Stern, I. Salomon, and P. Bovy (Eds.). Travel Behaviour: Patterns, Implications and Modelling.

El Mahrsi, M. K., Côme, E., Baro, J., and Oukhellou, L. (2014). Understanding passenger patterns in public transit through smart card and socioeconomic data: A case study in Rennes, France. In ACM SIGKDD Workshop on Urban Computing.

Eldeeb, G., & Mohamed, M. (2020). Quantifying preference heterogeneity in transit service desired quality using a latent class choice model. Transportation Research Part A: Policy and Practice, 139, 119-133.

Ettema, D and Timmermans, H (1997). Theories and models of activity patterns. In Ettema, D and Timmermans,H (eds.). Activity-based approaches to travel analyses, Pergamon.

Ettema, D., Borgers, A., & Timmermans, H. (1996). SMASH (Simulation model of activity scheduling heuristics): Some simulations. Transportation research record, 1551(1), 88-94.

Federal Highway Administration (2002). Status of the Nation's Highways, Bridges, and Transit: Conditions & Performance. http://www.fhwa.dot.gov/policy/ 2002cpr/pdf/execsummary_book.pdf. Accessed Dec 24, 2018.

Federal Highway Administration (2017). 2017 National Household Travel Survey, U.S. Department of Transportation, Washington, DC. [WWW Document]. URL https://nhts.ornl.gov (accessed March 1, 2018)

Frank, L., Bradley, M., Kavage, S., Chapman, J., and Lawton, T. K. (2008). Urban form, travel time, and cost relationships with tour complexity and mode choice. Transportation, 35(1), 37-54.

Fujii, S. and Kitamura, R. (2000). Evaluation of trip-inducing effects of new freeways using a structural equations model system of commuters' time use and travel. Transportation Research Part B: Methodological, 34(5), 339-354.

Golob, T. F. (2003). Structural equation modeling for travel behavior research. Transportation Research Part B: Methodological, 37(1), 1-25.

Golob, T. F. and McNally, M. G. (1997). A model of activity participation and travel interactions between household heads. Transportation Research Part B: Methodological, 31(3), 177-194.

Goulet-Langlois, G., Koutsopoulos, H. N., and Zhao, J. (2016). Inferring patterns in the multi-week activity sequences of public transport users. Transportation Research Part C: Emerging Technologies, 64, 1-16.

Goulias, K. G. and Kitamura, R. (1991). Recursive model system for trip generation and trip chaining. Transportation Research Record, 1236, 59-66.

Grahn, R., Hendrickson, C., Qian, Z. S., & Matthews, H. S. (2019). Socioeconomic and Usage Characteristics of Public Transit Riders in the United States. Presented at 98th Annual Meeting of the Transportation Research Board, Washington, D.C.

Hadiuzzaman, M., Farazi, N. P., Hossain, S., Barua, S., and Rahman, F. (2019). Structural equation approach to investigate trip-chaining and mode choice relationships in the context of developing countries. Transportation Planning and Technology, 42(4), 391-415.

He, L., Agard, B., and Trépanier, M. (2020). A classification of public transit users with smart card data based on time series distance metrics and a hierarchical clustering method. Transportmetrica A: Transport Science, 16(1), 56-75.

Hensher, D. A. and Reyes, A. J. (2000). Trip chaining as a barrier to the propensity to use public transport. Transportation, 27(4), 341-361.

Ho, C. Q. & Mulley, C. (2013). Multiple purposes at single destination: A key to a better understanding of the relationship between tour complexity and mode choice. Transportation Research Part A: Policy and Practice, 49, 206-219.

Hu, L. T. and Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural equation modeling: a multidisciplinary journal, 6(1), 1-55.

Islam, M. T. and Habib, K. M. N. (2012). Unraveling the relationship between trip chaining and mode choice: evidence from a multi-week travel diary. Transportation Planning and Technology, 35(4), 409-426.

Jiang, S., Ferreira, J., & González, M. C. (2012). Clustering daily patterns of human activities in the city. Data Mining and Knowledge Discovery, 25(3), 478-510.

Joh, C. H., Arentze, T., & Timmermans, H. (2001). Pattern recognition in complex activity travel patterns: comparison of Euclidean distance, signal-processing theoretical, and multidimensional sequence alignment methods. Transportation Research Record, 1752(1), 16-22.

Joh, C. H., Arentze, T., & Timmermans, H. (2004). Activity-travel scheduling and rescheduling decision processes: empirical estimation of Aurora model. Transportation Research Record, 1898(1), 10-18.

Kaplan, D. (2008). Structural equation modeling: Foundations and extensions (Vol. 10). Sage Publications.

Kitamura, R. (1988). An evaluation of activity-based travel analysis. Transportation, 15(1), 9-34.

Kline, R. B. (2016). Principles and practice of structural equation modeling. Guilford publications, New York, USA.

Krizek, K. J., & El-Geneidy, A. (2007). Segmenting preferences and habits of transit users and non-users. Journal of public transportation, 10(3), 5.

Krygsman, S., Arentze, T., & Timmermans, H. (2007). Capturing tour mode and activity choice interdependencies: A co-evolutionary logit modelling approach. Transportation Research Part A: Policy and Practice, 41(10), 913-933.

Kuppam, A. R. and Pendyala, R. M. (2001). A structural equations analysis of commuters' activity and travel patterns. Transportation, 28(1), 33-54.

Lanza, S. T., and Rhoades, B. L. (2013). Latent class analysis: an alternative perspective on subgroup analysis in prevention and treatment. Prevention Science, 14(2), 157-168.

Lee, M. S. and McNally, M. G. (2003). On the structure of weekly activity/travel patterns. Transportation Research Part A: Policy and Practice, 37(10), 823-839.

Lee, Y., Circella, G., Mokhtarian, P. L., and Guhathakurta, S. (2019). Are millennials more multimodal? A latent class cluster analysis with attitudes and preferences among millennial and generation X commuters in California. Transportation, https://doi.org/10.1007/s11116-019-10026-6

Levinson, D. and Kumar, A. (1995). Activity, travel, and the allocation of time. Journal of the American Planning Association, 61(4), 458-470.

Liao, F. H., Farber, S., and Ewing, R. (2015). Compact development and preference heterogeneity in residential location choice behaviour: A latent class analysis. Urban Studies, 52(2), 314-337.

Linzer, D. A., and Lewis, J. B. (2011). poLCA: An R package for polytomous variable latent class analysis. Journal of statistical software, 42(10), 1-29.

Lu, X. and Pas, E. I. (1999). Socio-demographics, activity participation and travel behavior. Transportation Research part A: policy and practice, 33(1), 1-18.

Ma, X., Liu, C., Wen, H., Wang, Y., and Wu, Y. J. (2017). Understanding commuting patterns using transit smart card data. Journal of Transport Geography, 58, 135-145.

Ma, X., Wu, Y. J., Wang, Y., Chen, F., and Liu, J. (2013). Mining smart card data for transit riders' travel patterns. Transportation Research Part C: Emerging Technologies, 36, 1-12.

Maat, K. and Timmermans, H. (2006). Influence of land use on tour complexity: a Dutch case. Transportation Research Record, 1977(1), 234-241.

Magidson, J. and Vermunt, J. (2002). Latent class models for clustering: A comparison with K-means. Canadian Journal of Marketing Research, 20(1), 36-43.

Martinez, L. M. and Viegas, J. M. (2017). Assessing the impacts of deploying a shared self-driving urban mobility system: An agent-based model applied to the city of Lisbon, Portugal. International Journal of Transportation Science and Technology, 6(1), 13-27.

McGuckin, N. and Murakami, E. (1999). Examining trip-chaining behavior: Comparison of travel by men and women. Transportation Research Record: Journal of the Transportation Research Board, (1693), 79-85.

McGuckin, N., Zmud, J., & Nakamoto, Y. (2005). Trip-chaining trends in the United States: understanding travel behavior for policy making. Transportation Research Record, 1917(1), 199-204.

McNally, M. G., and Rindt, C. (2008). The activity-based approach. In: D. A. Hensher and K. J. Button (Eds.). Handbook of Transport Modeling. 2nd ed., 55-73.

Mitra, S. K. and Saphores, J. D. M. (2017). Carless in California: Green choice or misery? Journal of transport geography, 65, 1-12.

Mokhtarian, P. L. and Cao, X. (2008). Examining the impacts of residential self-selection on travel behavior: A focus on methodologies. Transportation Research Part B: Methodological, 42(3), 204-228.

Morency, C., Trepanier, M., and Agard, B. (2007). Measuring transit use variability with smart-card data. Transport Policy, 14(3), 193-203.

Muthen, B. and Kaplan, D. (1992). A comparison of some methodologies for the factor analysis of non-normal Likert variables: A note on the size of the model. British Journal of Mathematical and Statistical Psychology, 45(1), 19-30.

NHTS Datasets (2017). National Household Travel Survey [WWW document] URL https://nhts.ornl.gov/ (accessed on July 1, 2019)

Noland, R. B. and Thomas, J. V. (2007). Multivariate analysis of trip-chaining behavior. Environment and Planning B: Planning and Design, 34(6), 953-970.

Noland, R.B., Schmocker, J.D. and Bell, M.G.H. (2008). Trip chaining behaviour of older people: Effects of medical conditions and urban form. Presented at 87th Annual Meeting of the Transportation Research Board, Washington, D.C.

Paleti, R., Bhat, C. R., and Pendyala, R. M. (2013). Integrated model of residential location, work location, vehicle ownership, and commute tour characteristics. Transportation research record, 2382(1), 162-172.

Pas, E. I. (1983). A flexible and integrated methodology for analytical classification of daily travel-activity behavior. Transportation science, 17(4), 405-429.

Pendyala, R. M., Kitamura, R., Kikuchi, A., Yamamoto, T., & Fujii, S. (2005). Florida activity mobility simulator: overview and preliminary validation results. Transportation Research Record, 1921(1), 123-130.

Pinjari, A. R., and Bhat, C. R. (2011). Activity-based travel demand analysis. A Handbook of Transport Economics, 10, 213-248.

Primerano, F., Taylor, M. A., Pitaksringkarn, L., & Tisato, P. (2008). Defining and understanding trip chaining behaviour. Transportation, 35(1), 55-72.

R Documentation. LavOptions.www.rdocumentation.org/packages/lavaan/versions/0.6-1.1240/topics/lavOptions. Accessed July 22, 2018.

Rafiq R. and McNally, M. G. (2020a). A study of tour formation: pre-, during, and post-recession analysis. Transportation. https://doi.org/10.1007/s11116-020-10126-8

Rafiq R. and McNally, M. G. (2020b). An Empirical Analysis and Policy Implications of Work Tours Utilizing Public Transit. Transportation Research part A: Policy and Practice (accepted for publication).

Rafiq, R., and McNally, M. G. (2018). Modeling the structural relationships of activity-travel participation of working women. Transportation Research Record, 2672(47), 81-91.

Ralph, K. M. (2017). Multimodal millennials? The four traveler types of young people in the United States in 2009. Journal of Planning Education and Research, 37(2), 150-163.

Recker, W. W. (1995). The household activity pattern problem: General formulation and solution. Transportation Research Part B: Methodological, 29(1), 61-77.

Recker, W. W., McNally, M. G., & Root, G. S. (1986a). A model of complex travel behavior: Part I—Theoretical development. Transportation Research Part A: General, 20(4), 307-318.

Recker, W. W., McNally, M. G., & Root, G. S. (1986b). A model of complex travel behavior: Part II—An operational model. Transportation Research Part A: General, 20(4), 319-330.

Ren, F., and Kwan, M. P. (2009). The impact of the Internet on human activity–travel patterns: analysis of gender differences using multi-group structural equation models. Journal of Transport Geography, 17(6), 440-450.

Saneinejad, S., & Roorda, M. (2009). Application of sequence alignment methods in clustering and analysis of routine weekly activity schedules. Transportation Letters, 1(3), 197-211.

Schneider, F., Ton, D., Zomer, L. B., Daamen, W., Duives, D., Hoogendoorn-Lanser, S., & Hoogendoorn, S. (2020). Trip chain complexity: a comparison among latent classes of daily mobility patterns. Transportation, 1-23.

Shiftan, Y., Outwater, M. L., & Zhou, Y. (2008). Transit market research using structural equation modeling and attitudinal market segmentation. Transport Policy, 15(3), 186-195.

Shoval, N., & Isaacson, M. (2007). Sequence alignment as a method for human activity analysis in space and time. Annals of the Association of American geographers, 97(2), 282-297.

Strathman, J. G., Dueker, K. J., & Davis, J. S. (1994) Effects of household structure and selected travel characteristics on trip chaining. Transportation, 21(1), 23-45.

Strathman, J. and Dueker, K. (1995). Understanding trip chaining. Special Reports on Trip and Vehicle Attributes, 1990 NPTS Report Series, US Department of Transportation and Federal Highway Administration.

Susilo, Y. O. and Kitamura, R. (2008). Structural changes in commuters' daily travel: The case of auto and transit commuters in the Osaka metropolitan area of Japan, 1980–2000. Transportation Research Part A: Policy and Practice, 42(1), 95-115.

TRB. (2007). Metropolitan Travel Forecasting: Current Practice and Future Direction--Special Report 288 (No. 288). Transportation Research Board.

Thuillier, E., Moalic, L., Lamrous, S., & Caminada, A. (2017). Clustering weekly patterns of human mobility through mobile phone data. IEEE Transactions on Mobile Computing, 17(4), 817-830.

Van Acker, V. and Witlox, F. (2010). Car ownership as a mediating variable in car travel behaviour research using a structural equation modelling approach to identify its dual relationship. Journal of Transport Geography, 18(1), 65-74.

Van Acker, V. and Witlox, F. (2011). Commuting trips within tours: how is commuting related to land use?. Transportation, 38(3), 465-486.

Wallace, B., Barnes, J., & Rutherford, G. (2000). Evaluating the effects of traveler and trip characteristics on trip chaining, with implications for transportation demand management strategies. Transportation Research Record: Journal of the Transportation Research Board, (1718), 97-106.

Wang, R. (2015). The stops made by commuters: evidence from the 2009 US National Household Travel Survey. Journal of Transport Geography, 47, 109-118.

Wang, Y., Qin, K., Chen, Y., & Zhao, P. (2018). Detecting anomalous trajectories and behavior patterns using hierarchical clustering from taxi GPS data. ISPRS International Journal of Geo-Information, 7(1), 25.

Yang, M., Wang, W., Ren, G., Fan, R., Qi, B., and Chen, X. (2010). Structural equation model to analyze sociodemographics, activity participation, and trip chaining between household heads: survey of Shangyu, China. Transportation Research Record, 2157(1), 38-45.

Ye, X., Pendyala, R. M., & Gottardi, G. (2007). An exploration of the relationship between mode choice and complexity of trip chaining patterns. Transportation Research Part B: Methodological, 41(1), 96-113.

Yun, M. P., Chen, Z. H., and Liu, J. Y. (2014). Comparison of mode choice behavior for work tours and non-work tours considering trip chain complexity. Presented at 93th Annual Meeting of the Transportation Research Board, Washington, D.C.

Zhou, Y., Yuan, Q., Yang, C., & Wang, Y. (2021). Who you are determines how you travel: Clustering human activity patterns with a Markov-chain-based mixture model. Travel Behaviour and Society, 24, 102-112.

Data Management Plan

This research used 2017 National Household Travel Survey (NHTS) data to conduct necessary analysis. This dataset is publicly available at: https://nhts.ornl.gov/downloads