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Exploring Activity-Travel Chaining Behavior: Classification, Peak-period Travel Implications, and Ride-hailing's Role

Author
Ahmed, Tanjeeb

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Exploring Activity-Travel Chaining Behavior: Classification, Peak-period Travel Implications, and Ride-hailing's Role

DISSERTATION

submitted in partial satisfaction of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

in Transportation Science

by

Tanjeeb Ahmed

Dissertation Committee:
Assistant Professor Michael F. Hyland, Chair
Professor Jean-Daniel Saphores
Professor Michael G. McNally

2024

DEDICATION

To

my family

in recognition of their unconditional love and unwavering support

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The road to PhD degree is long and can be tedious. But it can be enjoyable, exciting and peaceful with the support and mentorship of a great advisor. I have the same exact experience as my advisor, Professor Michael F. Hyland, supported me in every difficulty with his kind words, encouragement and with everything at his disposal. He is patient, understanding and one of the best human beings I have ever met. From him I not only learned how to be a good researcher but also learned how to be a good human being. I have never felt vulnerable during any stressful situation, which is common in a long PhD journey. And for this I feel blessed. Thank you very much Professor Hyland!

I would like to show my gratitude to my committee members, Professor Jean-Daniel Saphores and Professor Michael G. McNally, who helped me to improve my dissertation in the best possible way. Apart from this, every class and every discussion with them has been thought-provoking and a great learning experience for me.

I will forever be grateful to my family who are my lifeline and motivation for everything. Without the unconditional love, sacrifices and support of my parents, I would not even be in this position. They are the reason I dreamed to go abroad and earn a PhD degree. I am also very grateful to my wife for her unwavering support and encouragement through all my difficulties and carry out my research work. She single-handedly took care of everything and let me devote more time in my work. I feel lucky to have her by my side in this journey. My daughter and my son are two of my biggest inspiration for anything I do. They have been very supportive through this journey and with just a smile they immediately make me the happiest person in the world! I'm also grateful to my sister who has been my buddy for many casual talks and a source of encouragement. She has been there to look after my parents when I could not be present to offer any help.

I would also like to express gratitude to my mentors and colleagues, Dr. Suman Kumar Mitra, Dr. Rezwana Rafiq, Dr. Farzana Khatun and Dr. Yusuf Sarwar, who have been more like family to me. They have been with me through every major decision and predicaments long before I started my PhD program. They are also one of my biggest encouragements towards starting my PhD journey in UCI.

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I am grateful to Institute of Transportation Studies (ITS) and all of its members. I am proud to call ITS as my department as I always feel a sense of belongingness with it. This feeling is due to the courteous and helpful faculties, staffs and fellow students. I especially want to thank Cam and Jared for helping me with various administrative process, and Koti and Nav for their continuous support and encouragement.

Last the but not the least, I would like to thank the four metropolitan planning organizations, namely Chicago Metropolitan Agency for Planning (CMAP), Puget Sound Regional Council (PSRC), Sacramento Area Council of Governments (SACOG), and Whatcom Council of Governments (WCOG), for sharing their household travel survey data to support Chapter 3 and Chapter 4 of my dissertation.

VITA

TANJEEB AHMED

EDUCATION

Ph.D. in Transportation Science (2023)

Institute of Transportation Studies, University of California, Irvine.

Research Topic: Exploring Activity-Travel Chaining Behavior: Classification, Peak-period Travel Implications, and Ride-hailing's Role.

M.S. in Transportation Science (2017)

Institute of Transportation Studies, University of California, Irvine.

Research Topic: Exploring the Factors Affecting Bus Ridership in Orange County.

Master of Urban & Regional Planning (2016)

Bangladesh University of Engineering & Technology, Dhaka.

Research Topic: Exploring Trip Chain Behavior of the Working Population in Dhaka.

Bachelor of Urban & Regional Planning (2012)

Bangladesh University of Engineering & Technology, Dhaka.

Research Topic: Willingness to Pay for Retrofitting Against Earthquake Damage – A Study of Ward 68 of Dhaka City Corporation

RESEARCH INTERESTS

- Exploring the evolution of travel behavior with the advancement of technology and modes.
- Equity implications of emerging transportation modes
- Spatial analysis of transport-land use interaction
- Agent- and activity-based travel demand modeling

RESEARCH EXPERIENCE

- Working as a graduate student researcher in the project “Equity Analysis using Agent-based Models: Application to Robo-taxis and Job Access”.
- Working as a graduate student researcher in the project “AI-Based Mobility Monitoring System and Analytics Demonstration Pilot”.
- Working as a graduate student researcher in the project “Development of Modeling Framework to Assess Impacts of Congestion Pricing Policies on Transport Systems with New Mobility Options”, funded by the State of California via the Public Transportation Account and the Road Repair and Accountability Act of 2017 (Senate Bill 1).
- Worked as a graduate student researcher in the project “Quantifying the Employment Accessibility Benefits of Shared Automated Vehicle Mobility Services: Consumer Welfare Approach using Logsums”, funded by the State of California via the Public Transportation Account and the Road Repair and Accountability Act of 2017 (Senate Bill 1) (in 2019).

- Worked as a graduate student researcher in the project “Transportation Plans: Their Informational Content and Use Patterns in Southern California”, funded by Pacific Southwest Region UTC (in 2018).
- Worked as a researcher (transport and GIS) in the project “Planning and Prioritization of Rural Roads in Bangladesh”, conducted by the Department of Urban and Regional Planning, BUET, funded by ReCAP (in 2016).
- Worked as a researcher in Traffic Impact Assessment part of the feasibility study for the proposed new campus of BRAC University in Dhaka, conducted by the Department of Urban and Regional Planning, BUET (in 2014).

TEACHING EXPERIENCE

- Worked as an instructor in the Department of Urban and Regional Planning, BUET (2012-2016). During this time, I taught various courses including three undergraduate-level transportation courses comprising fundamental concepts, travel demand modeling techniques, and surveying techniques. Other courses I have taught include geographic information system (GIS) and statistics.
- Worked as a teaching assistant between 2018 and 2021 for the undergraduate courses CEE 121 and CEE 110, offered by the Department of Civil and Environmental Engineering, University of California, Irvine. For these courses, I had the responsibility to grade exams, supervise highway design projects (CEE 121), and conduct lab sessions to teach highway design with AutoCAD Civil 3D (CEE 121), scheduling projects with Microsoft Project (CEE 110), and solve linear programming with Microsoft Excel Solver Add-in.

CONFERENCE PRESENTATIONS

Ahmed, T., Hyland, M. (2023). Multi-Criteria Clustering of Trip Chains: Latent Class Analysis Using Four Household Travel Surveys. *Presented by T Ahmed at the 5th Bridging Transportation Researchers (BTR) Conference*.

Ahmed, T., Hyland, M. (2022). Equity Implications of Shared Automated Vehicle Mobility Services on Job Accessibility. *Presented by T Ahmed at the 4th Bridging Transportation Researchers (BTR) Conference*.

Rafiq, R., **Ahmed, T.**, & Uddin, M.Y.S. (2022). A Structural Analysis of COVID-19 Spread and Human Mobility in the Early Phase of the Pandemic. *Transportation Research Board (TRB) 101st Annual Meeting.* Washington, D.C.

Rafiq, R., McNally, M.G., Uddin, M.Y.S., & **Ahmed, T**. (2022). Flattening the Curve by Working from Home: Changes in Activity-Travel Behavior during the COVID-19 Pandemic. *Transportation Research Board (TRB) 101st Annual Meeting.* Washington, D.C.

Ahmed, T., Hyland, M., Sarma, N. J., Mitra, S., & Ghaffar, A. (2021). Assessing the Employment Accessibility Benefits of Shared Automated Vehicle Mobility Services in Southern California. *Presented by T Ahmed at the Transportation Research Board (TRB) 100th Annual Meeting.* A Virtual Event.

Ahmed, T., Hyland, M. (2021). Trip-Activity-Travel Chain Complexity, Technology Use, and Their Impacts on Ride-Hail Usage: A Structural Equation Model Approach. *Presented by T Ahmed at the Transportation Research Board (TRB) 100th Annual Meeting.* A Virtual Event.

Ahmed, T., Rafiq, R., & Jahan, S. (2021). Classification of Workers Based on Trip Chain Behavior in A Developing Country City. *Presented by T Ahmed at the Transportation Research Board (TRB) 100th Annual Meeting.* A Virtual Event.

Ahmed, T., Mitra, S. K., Rafiq, R., & Islam, S. (2020). Trip Generation Rates of Land Uses in a Developing Country City. *Presented by SK Mitra at the Transportation Research Board (TRB) 99th Annual Meeting.* Washington, D.C.

Ahmed, T., Hyland, M. (2020). Exploring the Role of Ride-Hailing in Trip Chains. *Presented by M Hyland at the Transportation Research Board (TRB) 99th Annual Meeting.* Washington, D.C.

Ahmed, T., Shil, B. C., Fahad, Z. H., & Akther, M. S. (2013). Modelling Willingness to Pay for Retrofitting: A Study of Ward 68 of Dhaka City Corporation. *Presented by T Ahmed at the Bridging the Policy-Action Divide: Challenges and Prospects for Bangladesh.* Berkeley, California: BDI.

PEER-REVIEWED PUBLICATIONS

Rafiq, R., McNally, M.G., Uddin, M.Y.S., **Ahmed, T**. (2022). Impact of Telecommuting on Activity-travel Behavior During the COVID-19 Pandemic: An Aggregate Structural Analysis. *Transportation Research Part A: Policy and Practice, 159,* 35-54. https://doi.org/10.1016/j.tra.2022.03.003

Ahmed, T., Hyland, M. (2022). Exploring the Role of Ride-Hailing in Trip Chains. *Transportation.* https://doi.org/10.1007/s11116-022-10269-w

Hasan, M.M.U., Quium, A.A., Rahman, M., Khatun, F., Akther, M.S., Haque, A., Jahan, S., Islam, I., **Ahmed, T.** and Shubho, T.H. (2022). A Methodology for Planning and Prioritisation of Rural Roads in Bangladesh. Sustainability, *14*(4), 2337. https://doi.org/10.3390/su14042337

Rafiq, R., **Ahmed, T**., Uddin, M.Y.S. (2022). Structural modeling of COVID-19 spread in relation to human mobility. *Transportation Research Interdisciplinary Perspectives, 13, 100528.* https://doi.org/10.1016/j.trip.2021.100528

Ahmed, T., Hyland, M., Sarma, N. J., Mitra, S., Ghaffar, A. (2020). Quantifying the employment accessibility benefits of shared automated vehicle mobility services: Consumer welfare approach using logsums. *Transportation Research Part A: Policy and Practice*, *141*, 221-247.

Ahmed, T., Mitra, S. K., Rafiq, R., Islam, S. (2020). Trip Generation Rates of Land Uses in a Developing Country City. *Transportation Research Record*, *2674*(9), 412-425.

Zannat, K., **Ahmed, T.**, Mitra, S. K., Rafiq, R., Hasan, M., Akhter, K., Fahad, Z. H. (2013). Parking Demand and Supply Analysis of Major Shopping Centers in Dhaka - A Case Study of New Market Shopping Center along Mirpur Road. *Journal of Bangladesh Institute of Planners*, 161-172.

AWARDS/HONORS RECEIVED

- Received the 2023 COMTO National Scholarship.
- Earned third place as a team in the COVID-19 Grand Challenge hosted by C3.ai for the project on "Structural Modeling of COVID Spread in Relation to Human Mobility" (2020).

- Received Fulbright Scholarship to pursue an MS in Transportation Science in ITS at the University of California, Irvine, for the 2016-17 academic year.
- Received research grant from BUET, Dhaka for conducting MURP thesis on “Exploring Trip Chain Behavior of the Working Population in Dhaka” (2015-2016).

PROFESSIONAL SERVICE

Served as a reviewer for:

- Transportation Research Part A – 1 paper review in 2023
- Transport Policy – 1 paper review in 2023
- Travel Behavior and Society – 2 paper reviews in 2023
- Transportation Research Record – 5 paper reviews in 2021-2023
- Transportation Research Board Annual Meeting – 3 paper reviews in 2022-2023
- Bridging Transportation Researchers (BTR) Conference – 5 paper reviews in 2022-2023

COMPUTER/SOFTWARE SKILLS

- Proficient in Microsoft Office, STATA, R, SPSS, ArcGIS, and AutoCAD
- Basic knowledge of C++ and Python

ABSTRACT OF THE DISSERTATION

Exploring Activity-Travel Chaining Behavior: Classification, Peak-period Travel Implications, and Ride-hailing's Role

by

Tanjeeb Ahmed

Doctor of Philosophy in Transportation Science

University of California, Irvine, 2024

Assistant Professor Michael F. Hyland, Chair

An activity-travel chain is a series of consecutive trips to multiple destinations. By influencing activity decisions (e.g., activity location, duration, and start time) and travel decisions (e.g., trip mode, route, and departure time), activity-travel chaining can directly impact roadway congestion, vehicle miles traveled by mode, transit ridership, energy consumption, and emissions of harmful pollutants.

In this context, my dissertation uses the 2017 National Household Travel Survey (NHTS) and 2018-2019 Household Travel Survey from four Metropolitan Planning Organizations (MPOs) to (i) identify distinct activity-travel chain types, (ii) quantify the effect of activity-travel chaining propensity on peak and off-peak person-miles traveled (PMT), and (iii) explore how activity-travel chain makers use emerging transportation modes (i.e., ride-hail). To perform these three analyses, I employ several statistical modeling techniques, including Latent Class Analysis (LCA), multi-level Poisson regression, structural equation modeling, and logistic regression.

In Chapter 3, I identify four distinct types of activity-travel chains. The most representative type involves simple car-based activity-travel chains with short-duration stops, typically for maintenance activities. The classification also reveals one group that exclusively represents non-motorized transport (NMT)- and transit-based activity-travel chains. In addition to identifying distinct activity-travel chains, I also model the propensity of travelers to conduct each type of activity-travel chain. I find that travelers in households with children and older travelers more frequently make car-based activity-travel chains for maintenance activities. Moreover, travelers in single-member households, and travelers who are younger and male more frequently make NMT- and transit-based activity-travel chains for maintenance activities. I expect the identification of these distinct activity-travel chain types, and the models of propensity of travelers to perform each activity-travel chain type, to be useful in agent- and activity-based travel forecasting modeling frameworks.

In Chapter 4, I investigate the structural relationship between activity-travel chaining propensity and motorized person-miles traveled (PMT) during the peak and off-peak periods of the day. Moreover, I differentiate between workers and non-workers. Using structural equation modeling techniques, and mediating factors I find that chaining of maintenance and discretionary activities increases peak motorized PMT for workers and non-workers, providing the strongest evidence in the literature that activity-travel chaining can exacerbate traffic congestion during peak travel periods. Moreover, I find possible substitution of maintenance activities (e.g., shopping, dining, etc.) in peak-hour with same/similar chained activities in off-peak hour.

Finally, in Chapter 5, I analyze activity-travel chain mode choice and show that young persons, frequent transit users, and those having long-duration stops prefer ride-hailing over car. Also, activity-travel chain makers headed to healthcare and social/recreational activities have a particularly high tendency to use ride-hail. Understanding the use of ride-hailing in activity-travel chains should help in formulating policies to better align ride-hailing services with compatible activity-travel patterns and consequently improve accessibility and mobility.

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

An activity-travel chain is a series of connected trips, which occurs when multiple out-of-home activities are grouped between two primary activities. For example, if a person stops for groceries on the way from work to home, this is an activity-travel chain, with two primary activities—work and home—and one secondary activity—grocery shopping. The main reason travelers chain activities is to save time and travel costs (Wang, 2015a). In a sense, activity-travel chaining is a way to maximize the utility of activity participation and travel between activities.

Early research on activity-travel chains goes back to the 1970s (Adler & Ben-Akiva, 1979; Lerman, 1979; Sasaki, 1971), with earlier acknowledgements in the 1960s (Thill & Thomas, 1987). Since then, studies have found that activity-travel chaining significantly influences travel characteristics, such as mode choice (Currie & Delbosc, 2011a; Hensher & Reyes, 2000; M. Lee & McNally, 2006), activity location (Huang & Levinson, 2017) and VMT (Duncan, 2016). By grouping multiple activities and trips together, the impact of activity-travel chaining is spatio-temporal in nature—trips to multiple locations are allocated within a certain time period, which could have been dispersed over a larger range of hours or days. Addressing this aspect of activity-travel chaining, Recker et al. (1987) classifies activity patterns based on 14 indices that reflects the spatial and temporal characteristics of activity pattern. They use *k*-means clustering algorithm on 665 observations from the Orange County area and identifies five clusters of individuals considering their activity patterns. The most dominant cluster, representing 45% of observations, has the highest number of trips and chained activities.

Over the years, we see considerable increase in activity-travel chaining and congestion. Activity-travel chaining has become more frequent and complex, thereby increasing the potential impacts of activity-travel chaining on the transportation system. The National Household Survey Dataset reveals that 33% more workers form activity-travel chains in their commute in 2017 compared to 2009. Moreover, a study based on Tampa Bay, Florida, finds that activity-travel chaining increases commute travel time by 70% (Hu & Li, 2021). On the other hand, traffic congestion has increased considerably over the last few decades despite various mitigation efforts (e.g., adding express lanes, increasing highway capacity, providing flexible work time option) (Chang et al., 2017). The increase in congestion is usually attributed to increased job opportunities, vehicle ownership and inadequate supply and maintenance of transportation infrastructures (Rahman et al., 2022). Researchers have also indicated the potential contribution of activity-travel chaining to increased congestion in peak hours when workers add activities to their commute trips (Currie & Delbosc, 2011a; Wang, 2015a). In addition, studies also find non-workers adding significant traffic to the road transportation system (Daisy et al., 2018).

1.2 Research Questions

The aforementioned context motivated the three main research questions I address in this dissertation:

i. What are the prevailing types of activity-travel chains as characterized by the activity and travel characteristics within activity-travel chains?
ii. How does activity-travel chaining affect peak and off-peak travel demand?

iii. What attributes of riders and activity-travel chains are associated with the choice of ride-hailing in activity-travel chains?

To answer these questions, I carry out a comprehensive analysis of prevailing activity-travel chaining patterns and their direct and indirect impacts on mode choice and person miles traveled (PMT) using the 2017 National Household Travel Survey (NHTS) and 2018-2019 household travel surveys from four Metropolitan Planning Organizations (MPOs). The four MPOs include the Chicago Metropolitan Agency for Planning (CMAP), the Puget Sound Regional Council (PSRC), the Sacramento Area Council of Governments (SACOG), and the Whatcom Council of Governments (WCOG). The objectives of my dissertation are to (i) identify distinct activity-travel chain types, (ii) quantify the effect of activity-travel chaining propensity on peak and off-peak person-miles traveled (PMT), and (iii) explore how activity-travel chain makers use emerging transportation modes (i.e., ride-hail). The outline of my dissertation is as follows.

1.3 Research Contributions and Dissertation Roadmap

In Chapter 3, I develop a modeling framework to classify prevailing activity-travel chains patterns with respect to multiple activity and travel attributes. Although, there are many studies analyzing the impacts of activity-travel chaining, only a few examine the existence of specific activity-travel chain types. Of those studies that do differentiate between activity-travel chain types, these studies typically only consider modes or a few travel attributes to characterize activity-travel chains. In contrast, I classify activity-travel chains considering a broader set of seven travel and activity characteristics (including activity-travel chain type, number of stops, dominant secondary activity, total activity duration, total travel distance, activity-travel chain mode, and travel day), using household travel survey data from four

MPOs and Latent Class Analysis (LCA) techniques. In addition, I investigate the propensity of travelers to conduct each activity-travel chain type by analyzing the effect of socio-demographic and location characteristics on the daily counts of each activity-travel chain category. For this analysis, I employ multi-level Poisson regression modeling using data from the same four MPOs.

In Chapter 4, I investigate the structural relationship between activity-travel chaining propensity and person miles traveled (PMT) with the inclusion of four mediating factors (i.e., travel time savings ratio, activity space area, average daily trips, and mode share). Of the many studies related to activity-travel chaining, most of them analyze its effect on trip complexity and mode choice (Currie & Delbosc, 2011a; Ye et al., 2007) and only a couple investigate impacts of activity-travel chaining on VMT (Concas & DeSalvo, 2014; Duncan, 2016), while none of them provide direct evidence of how activity-travel chaining impacts cumulative travel—measured in terms of PMT—during different times of day. As activity-travel chaining is a prominent travel behavior, knowing its direct impact on travel demand will help in formulating travel demand management policies. Motivated by this research gap and the importance of activity-travel chaining in modern transportation systems, I used the activity-travel chain dataset of the four MPOs and built a structural equation modeling (SEM) framework at the person level to investigate the relationship between activity-travel chaining propensity and motorized person-miles traveled (PMT) during the peak and off-peak periods of the day. I estimate separate models to differentiate the structural relationships between workers and non-workers. The results show that activity-travel chaining propensities of both workers and non-workers increase peak PMT. But there is a potential substitution of maintenance activities in peak hour with same or similar activities in off-peak hours. I also find that female workers have a higher activity-travel chaining propensity and peak motorized PMT than male workers.

In Chapter 5, I explore how activity-travel chain makers use ride-hailing (i.e., the base service offered by Uber and Lyft), an emerging transportation mode. Studies have already established the significant impact of activity-travel chaining on the choice of traditional modes, like car and transit. Specifically, because cars offer significant flexibility in trip scheduling and route choice many activity-travel chain makers rely on cars. However, evidence does suggest that activity-travel chain makers use transit in high density areas with limited or expensive parking (Currie & Delbosc, 2011a; Xianyu, 2013). Ride-hailing provides many of the advantages of a private car (schedule and routing flexibility, door-to-door service) without the drawbacks of vehicle ownership nor the parking concerns of a private car.. Given these advantages, ride-hailing is a potentially attractive mode in forming activity-travel chains. Therefore, my dissertation seeks to understand its current role in activity-travel chains, to inform policymakers and regulators as they seek to align the benefits of ride-hailing services with the activity-travel needs of travelers. As such, I use the 2017 National Household Travel Survey (NHTS) dataset to explore the socio-demographic characteristics of ride-hail users in trips chains, as well as the attributes of activity-travel chains and land use characteristics of activity-travel chain origins associated with ride-hailing. To analyze the data, I employ a binary logit model to explore the effects of socio-demographic characteristics, activity types, activity-travel chain attributes, mode attributes, and land use characteristics on the inclusion of ride-hailing in activity-travel chains. In addition, I also employ a nested logit model to explore the aforementioned effects on the choice of ride-hailing as a primary mode in activity-travel chains.

And lastly, in Chapter 6, I provide a summary of the findings from my three studies and discuss limitations in my research work and possible future research areas.

CHAPTER 2: DEFINITIONS AND TERMS

This chapter describes all the important definitions and terms used throughout the dissertation.

2.1 Activity-Travel Chain

I use two slightly different definitions of activity-travel chain, in this dissertation. The main difference between the definitions is in the inclusion of home and work activity locations as default anchors. Chapter 3 and Chapter 4 uses Definition 1. Chapter 5 uses Definition 2.

Definition 1: An activity-travel chain is defined as a series of two or more trips with one primary activity and at least one secondary activity. Primary activities are the ones that mark the start and end of an activity-travel chain. Stops at home or work locations always represent primary activities. Additionally, I consider any activity with a duration greater than four hours a primary activity. Hence, I classify all non-work and non-home activities with a duration of less than four hours as secondary activities.

Definition 2: An activity-travel chain is defined as a series of two or more trips with one primary activity and at least one secondary activity. Primary activities are the ones that mark the start and end of an activity-travel chain and are identified as activities with a duration greater than four hours. Hence, I classify all activities with a duration of less than four hours as secondary activities.

2.2 Activity-Travel Chaining Propensity

I define activity-travel chaining propensity as the tendency to include activities in activity-travel chains rather than having separate (unchained) trips for them. Activity-travel chaining propensity entails three variables that represent, respectively, the proportion of subsistence, maintenance, and discretionary activities carried out in chained trips as opposed to unchained trips. Subsistence activities represent school and work activities, which are usually time-constrained. Maintenance activities include shopping, errands, healthcare, escort, dining, etc., which have higher scheduling flexibility. Discretionary activities constitute leisure, social, and recreational activities and, therefore, are the most flexible to schedule.

2.3 Dominant Secondary Activity

In an activity-travel chain with multiple secondary activities, the dominant secondary activity is the one with the total longest duration within an activity-travel chain.

2.4 Primary Mode in an Activity-Travel Chain

The primary activity-travel chain mode is the mode used within the activity-travel chain that is used to travel the farthest distance across all trips within the activity-travel chain. This definition does not consider the number of trips made by each mode. Hence, an activity-travel chain with five trips in which the traveler makes four of the trips via walking may have a primary mode of automobile if the distance of the single automobile trip is greater than the cumulative distance of all four walk trips.

2.5 Secondary Mode in an Activity-Travel Chain

A secondary activity-travel chain mode is any mode used within the activity-travel chain other than the primary mode; the activity-travel chain maker travels less distance in a secondary activity-travel chain mode than in the primary mode.

2.6 Travel Time Savings Ratio

Travel time savings ratio (TTSR) represents the fraction of travel time saved by chaining activities as opposed to traveling to each activity separately in home-based round trips. I adopt the definition and equation for calculating TTSR from Huang and Levinson (2017). The equation below shows the TTSR formula for each person in the dataset (Eq. 1).

$$TTSR_i \frac{\sum_0^m tv_{i,m} - (\sum_0^j tc_{i,j} + \sum_0^k tu_{i,k})}{\sum_0^m tv_{i,m}} \tag{1}$$

In Eq. 1, tu and tc represent the travel times for unchained and chained trips, respectively, carried out by person i. Considering a person makes j chained trips and k unchained trips, the terms inside the parentheses in the numerator represent the total travel times. The term tv represents the calculated home-based round-trip travel times for all trips (m) carried out by that person, where (m=j+k). Hence, the numerator represents the travel time savings due to activity-travel chaining and the denominator represents the total travel time if all the trips were unchained.

To obtain the direct travel time between home and all activity locations, I used HERE Maps REST API (HERE, 2023) to calculate travel times between pairs of home and activity census tract centroids. All the travel times are for car trips based on HERE's fastest route algorithm. I requested the HERE Maps API through the community developed GEOROUTE command in STATA (Weber et al., 2022).

2.7 Home to Activity Center Distance

Home to Activity Center Distance is a measure of the overall proximity of a traveler's non-home activity locations to the traveler's home residence. It is calculated as the distance (in miles) from the home location to the centroid of all the non-home activity locations visited by a person in a given time period (e.g., day or week).

2.8 Mode Share

I created the mode share variables for NMT, auto, and transit by calculating the proportions of all trips in which each of these modes is used.

2.9 Activity Space Area

This dissertation uses a standard deviational ellipse (SDE) to measure the area of activity spaces (in square miles) formed by the activity locations visited by persons throughout a week, including their home locations. By using the mean coordinates of all the locations (including repetitions for multiple visits), SDE incorporates both clustering and frequency of visits to an activity location when determining its size and shape (Sherman et al., 2005).

2.10 Peak and Off-Peak Motorized Person Miles Traveled (PMT)

This dissertation defines the following peak travel periods that vary across the four MPOs considering the typical temporal distribution of trips in these areas.

- Chicago Metropolitan Agency for Planning (CMAP): 6:30 am to 9 am and 4 pm to 6 pm.
- Puget Sound Regional Council (PSRC): 7:30 am to 9:30 am and 4 pm to 7 pm.
- Sacramento Area Council of Governments (SACOG): 7:30 am to 9:30 am and 4 pm to 6:30 pm.
- Whatcom Council of Governments (WCOG): 7:30 am to 10:00 am and 4 pm to 6:30 pm

All other time periods are considered as off-peak. Peak (off-peak) motorized PMT is calculated as the total distance traveled by each person per day in the peak (off-peak) period using a motorized mode, where motorized modes include car, taxi, ridehail and shared modes in all trips. I used PMT instead of vehicle miles traveled (VMT) because, unfortunately, the data does not permit analysts to determine if a traveler is sharing a vehicle trip with household and non-household members.

CHAPTER 3: CLUSTERING ACTIVITY-TRAVEL CHAINS AND MODELING THE DAILY FREQUENCY OF EACH ACTIVITY-TRAVEL CHAIN TYPE

3.1 Introduction

As noted by several studies, the frequency of activity-travel chain formation has increased throughout the world. While the increased frequency is the result of travelers combining trips and activities together due to time and cost considerations, a city's land use distribution and traffic conditions play an important role in the formation of activity-travel chains (Strathman et al., 1994a). In a nationwide study using the 2001 National Household Travel Survey (NHTS) dataset, McGuckin et al. (2005) found that over 27% of the workers form activity-travel chains in their commute. This percentage increased to 60% in 2017 based on Ahmed and Hyland's (2022) analysis of NHTS data; I also find that activity-travel chains comprise 64% of all trips. Car-based commute trips with shopping/grocery and escort as secondary activities are the most common type of activity-travel chain (Ahmed & Hyland, 2022; Currie & Delbosc, 2011a; Schneider, Daamen, et al., 2021).

Activity-travel chaining has received frequent attention in the traveler behavior literature, as it directly impacts mode choice, trip distribution, VMT, congestion and other important system performance metrics. Policies to manage travel attributable to activity-travel chaining require an in-depth understanding of the types of activity-travel chain patterns that travelers make, as well as the socio-demographic, land use, and transportation system characteristics that influence the formation of such patterns. Thus, the complete realization of the impacts of activity-travel chains involves identifying their patterns by jointly characterizing activity-travel chain attributes. Characterizing activity-travel chains enables identifying the relationship between different trips and their attributes, which can help in forecasting travel demand.

Motivated by the opportunity to support travel demand management policies related to activity-travel chaining, this study classifies activity-travel chains based on the properties of activity-travel chains and their constituent trip segments. The Chapter combines activity-travel chain data from four metropolitan planning organizations (MPOs) across the country. The research methodology incorporates a latent class analysis (LCA) model, a multi-criteria activity-travel chain definition that comprises both activity duration and type, as well as travel attributes. The methodology also includes a multi-level Poisson model to analyze the predictors of class-specific activity-travel chain frequency. The main objectives of this chapter are to:

1. explore the existence of distinct activity-travel chain classes
2. potentially identify distinct classes of activity-travel chains
3. analyze activity-travel chain frequency alongside the socio-demographic, travel, and home location characteristics of activity-travel chain makers

Schneider et al. (2021) also categorize activity-travel chain makers using LCA, but their model distinguishes clusters considering only preference for travel mode and day, whereas I also include other activity-travel chain characteristics, such as the number of stops, activity/trip duration, and primary and secondary activity types, alongside mode(s).

3.2 Conceptualization of Activity-Travel Chaining and Data Preparation

I define an activity-travel chain as having one primary activity and one or more secondary activities. All activities with a duration greater than four hours are primary activities.

Additionally, this study treats home and primary work activities as primary activities irrespective of their duration, consistent with much of the literature (Gao et al., 2019; Hensher & Reyes, 2000; Xianyu, 2013). Secondary activities are non-home/-work activities with a duration of less than four hours.

I generate the activity-travel chain dataset for this study using 2018-2019 household travel survey (HTS) data from four MPOs in the United States, namely, Chicago Metropolitan Agency for Planning (CMAP), Puget Sound Regional Council (PSRC), Sacramento Area Council of Governments (SACOG), and Whatcom Council of Governments (WCOG). Each of the HTS datasets from these MPOs contains comprehensive activity-travel data at the trip level along with socio-demographic information for household members in the sample.

After applying the activity-travel chain definition and using several filters, the dataset for estimating the classification model (LCA) contains 47,251 activity-travel chains. Figure 1 shows the distribution of the chained trips across the four MPOs and also the proportion of chained trips compared to unchained trips. For estimating the prediction model (multi-level Poisson regression), I only use weekday data. Hence, the trimmed dataset for the prediction model contains 27,486 weekdays of observations pertaining to 19,469 persons making a total of 39,717 activity-travel chains.

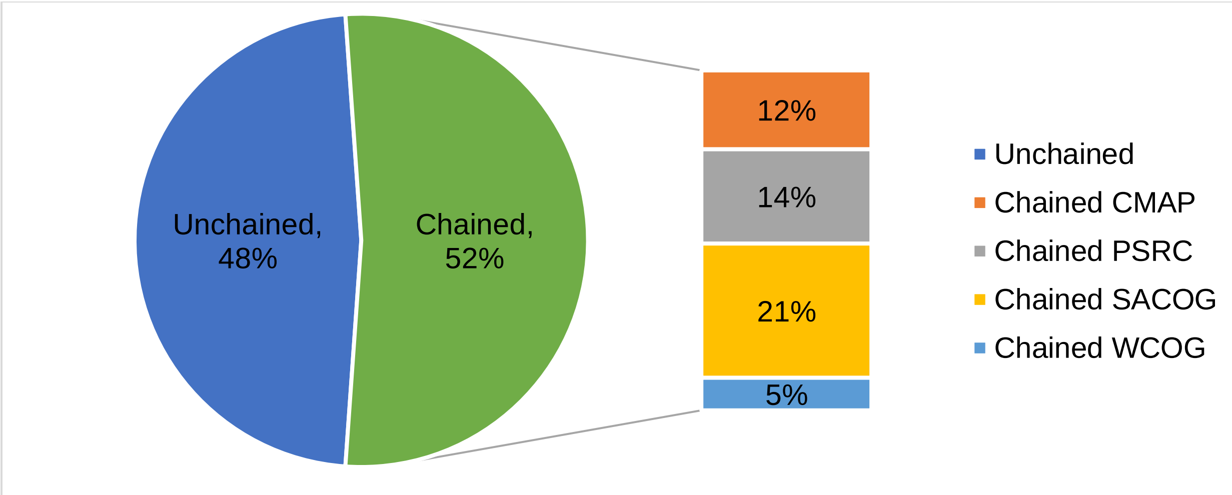


Figure 1: Distribution of Trips in Unchained and Chained Trips Across Four MPOs

3.3 Methodology

The modeling approach of this study consists of two sequential modeling steps. Step 1 comprises a classification model, built using latent class analysis (LCA) approach. This step divides the activity-travel chains into groups based on seven selected indicators of activity-travel chain. Step 2 comprises a prediction model formulated as a multi-level Poisson regression, where the outcome variables are the counts of activity-travel chains in each class that a person completes in a day. The predictors in this model are the socio-economic and home location characteristics of the activity-travel chain makers.

3.3.1 Step 1: Classification Model

This study uses LCA, which is a statistical modeling approach that classifies observations into mutually exclusive groups (aka segments, clusters, or classes). The name 'latent' in LCA comes from the unobserved heterogeneity in observations that this model reveals through a set of given manifest or indicator variables (Weller et al., 2020). An LCA model requires estimating two parameters representing class-conditional and prior class-membership probabilities for each of the responses of the indicator variables. The class conditional probability, π_{yvc}, is the probability of outcome y on indicator variable v given the membership in class c for a person, whereas, the prior class-membership probability, p_c, is the probability of a person assigned to class c without considering the responses on the indicator variables. Eq. 2 represents the general functional form of the LCA model that calculates the posterior class membership probability for individual n, $P(c_n|R_n)$. In this equation, R_n is the response pattern on a set of indicator variables by individual n and I_{nyv} represents an indicator function with value 0 (if $y_v \neq R_v$) or 1 (if $y_v = R_v$) and p_c acts as the weight.

$$P(c_n|R_n) = \frac{p_c \prod_{v=1}^{V} \prod_{y_v=1}^{Y_v} \left(\pi_{yvc}\right)^{I_{nyv}}}{\sum_{c=1}^{C} p_c \prod_{v=1}^{V} \prod_{y_v=1}^{Y_v} \left(\pi_{yvc}\right)^{I_{nyv}}} \tag{2}$$

I specify the LCA model with seven indicator variables pertaining to trip, activity, mode choice and travel day characteristics. Table 1 provides a list of these indicators along with their distribution across the four MPOs. Chapter 2 provides detailed definitions of the variables created for this study.

3.3.2 Step 2: Prediction Model

This study develops a multi-level Poisson regression to predict the frequency at which individuals make each type of activity-travel chain over the course of a (week)day. The prediction model considers the socio-economic and home location characteristics of the activity-travel chain makers as covariates. A multi-level Poisson modeling framework is suitable to address correlated observations that occur within a hierarchical data structure with the help of random intercepts (A. H. Lee et al., 2006). Before selecting a multi-level model, I ran a series of log-likelihood ratio tests between models with and without random intercepts with different structures. All chi-squared test statistics indicate the suitability of a multi-level or hierarchical modeling framework for this study.

Table 1: Distribution of the Selected Indicators for the LCA Model in the Study Area

Indicators	MPO				Total
	CMAP	PSRC	SACOG	WCOG	
Activity-Travel Chain Type					
To Home	78.21	82.39	82.47	85.65	81.53
To Non-Home	21.79	17.61	17.53	14.35	18.47
Number of Stops					
1-2	85.39	79.94	72.46	69.61	78.04
3 or more	14.61	20.06	27.54	30.39	21.96
Secondary Activity (with longest duration)					
Subsistence (S)	8.05	7.90	7.65	9.07	7.97
Maintenance (M)	69.71	61.52	58.49	54.82	62.22
Discretionary (D)	22.24	30.58	33.85	36.11	29.81
Total Activity Duration (mins)					
Up to 60	59.68	54.33	50.57	47.21	53.94
More than 60	40.32	45.67	49.43	52.79	46.06
Total Travel Distance (miles)					
Up to 10	56.76	62.92	55.25	56.54	58.01
10-25	27.28	24.29	26.96	27.43	26.32
More than 25	15.96	12.79	17.79	16.03	15.67
Activity-Travel Chain Mode					
NMT/Transit	16.38	29.02	11.42	9.07	17.70
Auto	78.65	62.72	80.62	82.58	75.06
Multimodal	4.97	8.26	7.96	8.35	7.23
Travel Day					
Weekday	100.00	81.91	74.62	75.95	84.06
Weekend	0.00	18.09	25.38	24.05	15.94

Eq. 3-5 represent the general functional form of a three-level Poisson regression model with day at the bottom level, person at the middle level, and household at the top level. Two random intercepts, one each for the person (α_j) and household (γ_k) levels, capture the correlations in the class-specific activity-travel chain counts with each level. I simultaneously estimate the four class-specific models as generalized linear mixed models (GLMM) using the expectation-maximization algorithm in Stata.

Level 1 (Day): $log\mu_{ijk} = \alpha_j + \gamma_k + \beta X_{ijk} + \varepsilon_{ijk}$ (3)

Level 2 (Person): $\alpha_j = \varphi + u_j$ (4)

Level 3 (Household): $\gamma_k = \vartheta + w_k$ (5)

where,

μ_{ijk} = expected value of counts for day *i*, person *j* and household *k*
X_{ijk} = explanatory variables at level 1
α_j, γ_k = fixed intercepts for person and household levels, respectively
u_j, w_k= random error terms for person and household levels, respectively
ε_{ijk} = random error term at level 1

3.4 Results

This section discusses the results from the LCA and multi-level Poisson Model.

3.4.1 Estimation of LCA

Using the indicators listed in Table 1, this study estimates the LCA model with the help of the *poLCA* package in *R*. The estimation process includes multiple LCA models with class sizes ranging from 1 to 10 that I compare with respect to goodness-of-fit measures and classification outcomes. For optimizing between attaining global maxima and reducing computational time, I estimate each model thirty times with different random initial class-conditional probability matrices for each indicator. For each class size, the best model is the one with the highest log-likelihood. Figure 2 shows the plots of BIC (left *y*-axis) and entropy R^2 (right y-axis) with respect to the 10 LCA models for classes 1 through 10 (*x*-axis). BIC or Bayesian Information Criteria is based on the log-likelihood function and penalizes against the number of model parameters when comparing different model specifications (Kaplan & Keller, 2011). A lower value of BIC represents good model. Entropy R^2 is a measure of the relative error in the class assignments (Kaplan & Keller, 2011). Therefore, a higher value, preferably greater than 0.50, indicates better model providing distinct classes (Bakk & Kuha, 2021).

After obtaining all the class-specific models, the model with four classes appears to provide the best classification of activity-travel chains in terms of statistical fit and parsimony. The four class model has the highest and preferred value of entropy R^2 (0.75); moreover, the change in BIC is comparatively low after four classes, and it also provides the most comprehensible class interpretation. Studies conducted with LCA commonly use these goodness-of-fit measures for comparing the overall model fit and their classification quality (Bakk & Kuha, 2021; Kaplan & Keller, 2011).

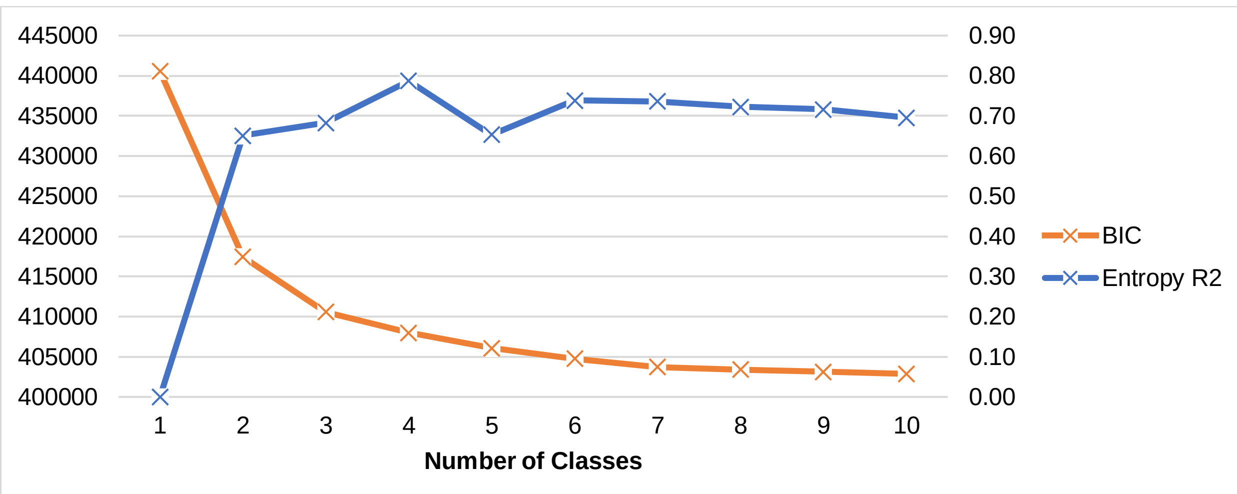


Figure 2: Goodness-of-fit Statistics of the LCA Models for Class 1 to 10

In addition, researchers also use posterior probabilities of the observations for the classes to verify the accuracy of the classification. This verification is achieved with the help of a posterior probability matrix where the diagonal cells represent average posterior probabilities of the activity-travel chains in their assigned classes and the off-diagonal cells represent average posterior probabilities of the assigned activity-travel chains in other classes (Muthen & Muthen, 2000). Thus, a higher probability (i.e., close to 1) is preferable for the diagonal cells and a lower probability (i.e., close to 0) is preferable for off-diagonal cells. While probability values greater than 0.90 are generally accepted for diagonal cells, Weller et al. (2020) argues that the cut-off point can be lowered to 0.80 if the model satisfies other criteria. Table 2 shows the posterior probability matrix for the selected four-class LCA model where all the values exceed the 0.80 threshold.

Table 2: Posterior Probability Matrix

Class	1	2	3	4
1	**0.961**	0.005	0.022	0.012
2	0.038	**0.914**	0.001	0.048
3	0.027	0.001	**0.880**	0.092
4	0.087	0.032	0.078	**0.803**

3.4.2 Identification of Classes from the LCA Model

Figure 3 shows class-conditional probabilities (CCPs) from the LCA model with six classes. The prior class-membership probabilities are 44%, 13%, 19% and 25%, respectively, for Classes 1 through 4.

Considering the magnitude of class-conditional probabilities across the indicators and the classes in Figure 3, I label the four classes as:

- Class 1: simple car-based activity-travel chains with one or two stops for short-duration errands
- Class 2: simple NMT/Transit-based activity-travel chains with one or two maintenance activity stops within 10 miles of the home location
- Class 3: complex half- to full-day errand activity-travel chains that also include discretionary activities
- Class 4: simple car-based weekday activity-travel chains with 1-2 stops for long-duration discretionary activities

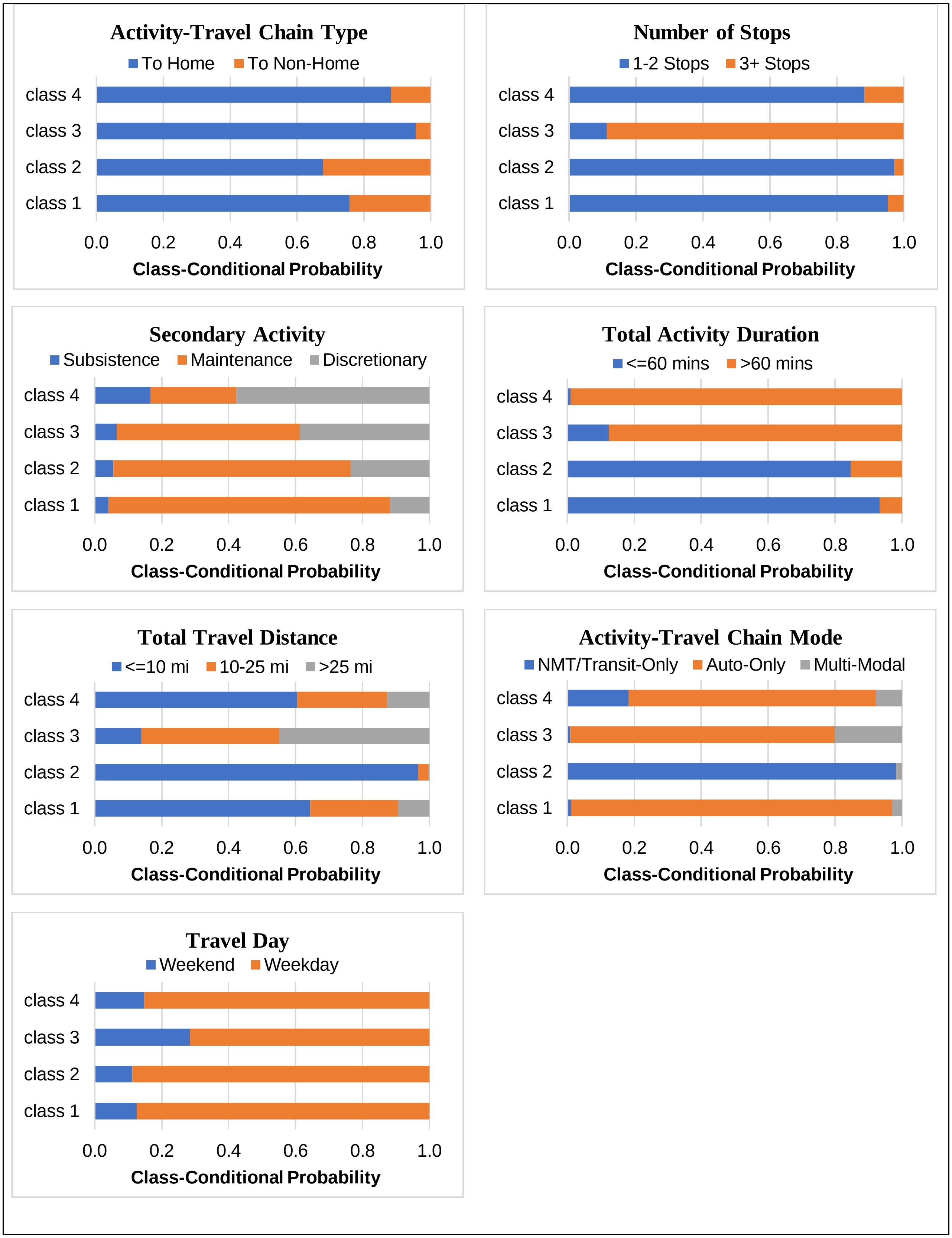


Figure 3: Class-Conditional Probabilities of the Seven Indicators

3.4.3 Prediction Model Results

Table 3 presents the coefficients, variances, and goodness-of-fit statistics from the prediction model. As expected from a multi-level model, there are some unexplained variations between persons and households, considering the class-specific activity-travel chain counts after controlling all predictors. Also, there is higher variation between households than persons, based on the estimates of variance of random-intercepts in Table 3.

Looking at the coefficients for Class 1, I see that people make more of these simple car-based activity-travel chains with one or two stops for short-duration errands activity-travel chains if they:

- are more than 55 years old,
- live in households with 0-4 year old children,
- live in households with more vehicles,
- commute to work on the travel day,
- live in areas with lower population density,
- live in areas with lower land use diversity, and
- live in areas with lower transit frequency.

Those who make more Class 2 activity-travel chains (simple NMT/Transit-based activity-travel chains with one or two maintenance activity stops within 10 miles of home) are more likely to be:

- male,
- below 55 years old,
- from a high-income household,
- living alone,
- without household vehicles
- workers

- living in areas with higher population density,
- living in areas with higher land use diversity, and
- living in areas with higher transit frequency.

Table 3: Prediction Model Results for Four Activity-Travel Chain Classes

Predictors	Coefficients			
	Class 1	Class 2	Class 3	Class 4
Household Income (base: Less than $50K)				
$50-$100K	0.006	0.071	-0.094***	0.045
$100K or more	-0.001	0.187***	-0.185***	0.122***
Household type (base: Single Member)				
Multi-member, no child	0.045*	-0.196***	-0.028	-0.025
Multi-member, youngest child 0-4 yrs	0.476***	-0.122**	0.026	-0.342***
Multi-member, youngest child 5-15 yrs	0.454***	-0.275***	0.036	-0.119***
Multi-member, youngest child 16-17 yrs	0.255***	-0.891***	-0.136	-0.008
Household vehicle per License (base: zero vehicle)				
Less than 1 vehicle	1.797***	-0.548***	0.745***	0.049
1 or more vehicle	1.992***	-1.069***	0.993***	0.006
Gender (base: Male)				
Female	-0.012	-0.128***	0.178***	0.060***
Age (base: below 55 years)				
55 years or above	0.047**	-0.169***	0.118***	-0.053**
Ethnicity/Race (base: Other Race)				
Non-Hispanic Black	-0.023	0.019	0.021	-0.137**
Work on Travel Day (base: no work activity)				
Telework only	-0.029	0.231***	-0.129***	-0.075**
At least one work trip	0.264***	0.216***	-0.746***	-0.124***
Home Location Characteristics (log-transformed)				
Population density	-0.178***	0.904***	-0.235***	0.121***
Land use diversity	-0.256***	0.846***	-0.011	0.031
Transit frequency	-0.014**	0.187***	0.004	-0.018**
Household-level random intercept	1.000	-1.029***	0.032	-0.932***
Person-level random intercept	1.000	-8.546*	-2.204*	3.055
constant	-2.680***	-2.095***	-1.890***	-1.025***
Variance of random intercept				
Household-level	0.124			
Person-level	0.005			
Model Goodness-of-fit				
Log-likelihood	-75092.768			
LR χ^2	984.592 ($p > \chi^2 = 0.000$)			
AIC	150337.500			
BIC	150962.300			

Sig. codes: '***' 0.01 '**' 0.05 '*' 0.10

Frequent Class 3 activity-travel chain (complex half- to full-day errand activity-travel chains that also include discretionary activities) makers are more likely to:

- be female,
- be aged over 55 years,

- be from a low-income household,
- have access to household vehicles,
- have no work activity on the travel day,
- live in a low population density area, and
- live in an area with low transit frequency.
- I also observe a negative effect of population density on the frequency of Class 3 activity-travel chains.

The findings suggest that activity-travel chain makers residing in areas with dispersed activity locations have a higher likelihood of forming complex, car-based, and long-distance activity-travel chains.

Finally, Class 4 activity-travel chains (simple car-based weekday activity-travel chains with 1-2 stops for long-duration discretionary activities) makers are more likely to:

- be female,
- be below 55 years,
- not be non-Hispanic Black,
- not have children, particularly those below 5 years,
- live in a high-income household,
- not work,
- live in dense areas, and
- live in an area with lower transit frequency.

3.5 Discussion and Conclusion

This study estimates an LCA model to categorize activity-travel chains using attributes of activities and trips that comprise activity-travel chains. Using the resulting classes, I specified a multi-level Poisson model to investigate the effect of household, person, and location characteristics on the frequency with which individuals conduct each of these types of activity-travel chains.

The results from the LCA models reveal the existence of four distinct groups of activity-travel chains and the prediction model indicates significant associations between the activity-travel chain classes and socio-economic and location characteristics. These findings have important policy implications. One evident and noteworthy finding is the prevalence of car-based activity-travel chains, with one or two stops ending at home locations for maintenance activities and the tendency of commuters to prefer more simple and short-distance activity-travel chains. Strathman et al. (1994a), McGuckin (2004), and Ahmed & Hyland (2022) also observe a similar distribution of activity-travel chains based on primary and secondary activities.

I also find that Class 3 has the highest and dominant representation of complex activity-travel chains with three or more stops. This class is also more multimodal than other classes and has longer trip and activity durations and a diverse range of secondary activities. Since weekend activity-travel chains have a noticeable share in this class, this suggests that people prefer multimodal activity-travel chains to stop for multiple long-duration activities when their travel schedules are less restricted due to the absence of work and school activities. Overall, this finding is consistent with the observations of Rafiq & McNally (2022a). Policies for transit-oriented development addressing these findings can help to improve mobility of all sections of the community, especially carless households, by reducing car dependency in complex trip making and peak-hour traffic congestions associated with car-based commute activity-travel chains (Currie & Delbosc, 2011a; Wang, 2015a).

The representation of activity-travel chain modes across classes presents some interesting findings. Unlike the general consensus in the existing literature, two (Class 1 and 4) out of the three highly car-based activity-travel chains have lower complexity in terms of number of stops. The difference originates from the distribution of total activity and trip distances across these classes. Apparently, people highly prefer cars in activity-travel chains if they need to travel longer to participate in multiple activities spread over large distances. Moreover, according to Table 3, households with children up to 15 years and people in older age groups have a noticeably high preference towards Class 1 activity-travel chains, while females prefer Class 4 activity-travel chains. Therefore, these groups of activity-travel chain makers are likely to experience a significant reduction in mobility when personal vehicles are inaccessible (e.g., due to parking costs). Hence, mobility improvement policies for this group should ensure the inclusion of accessibility and security measures in public transport and shared mobility services.

Although most activity-travel chains are predominantly car-based, there are substantial representations of NMT, transit, and multimodal activity-travel chains in Class 2-4. Most importantly, the existence of Class 2, which exclusively represents NMT and transit, is an indication that these modes are most convenient for activity-travel chains with short-duration maintenance and discretionary activities within 10 miles of the home location. On the contrary, classes with a considerable share of multimodal activity-travel chains are more likely to have longer trip and activity durations and frequent stops, all of which are clearly evident in Class 3. Schneider et al. (2021) also observe the high complexity of multimodal activity-travel chains, which they attribute to the use of secondary modes (e.g., bike) at work locations and the availability of ride-sharing and bike-sharing services.

This study includes limitations, which are mainly due to data unavailability. Firstly, without complete data on trip planning, this study could not distinguish between pre-planned and opportunistic stops in activity-travel chains. Knowing this information can help in correctly identifying the association between primary and secondary activities. Secondly, due to a large number of unavailable data on multi-day, it is difficult to verify the inclusion of all possible activity-travel chains in the study area. Future extensions of this study include adding a routing-based indicator of activity-travel chain complexity.

CHAPTER 4: EFFECTS OF ACTIVITY-TRAVEL CHAINING PROPENSITY ON PEAK AND OFF-PEAK MOTORIZED PERSON MILES TRAVELED: A COMPARISON BETWEEN WORKERS AND NON-WORKERS

4.1 Introduction

Activity-travel chaining is a prevailing component of travel behavior that is associated with mode preference, destination choice, and vehicle miles traveled (Ahmed & Hyland, 2022; Duncan, 2016; Huang & Levinson, 2017). Activity-travel chains are formed when additional stop(s) are added to a primary activity (or trip purpose) in order for the traveler to decrease their overall travel time and cost. Huang & Levinson (2017) found that the land use characteristics of destination and the travel time saved by adding separate trips into chains play an important role in adding destinations in activity-travel chains. Regarding vehicle miles traveled and activity-travel chaining, there are mixed findings on the direction of the effect (Duncan, 2016; Kim et al., 1994).

Although there is a rich literature on activity-travel chaining, very few studies investigate activity-travel chaining beyond mode choice and trip complexity. Some studies have suggested that activity-travel chaining can exacerbate peak-hour congestion, particularly when stops are added to commute trips (Currie & Delbosc, 2011a; Wang, 2015a). In addition, non-workers can add significant traffic to the road transportation system (Daisy et al., 2018). But none of these studies directly measured the contribution of activity-travel chaining on congestion in peak or off-peak hours. In this context, this study builds a structural equation model (SEM) to analyze the hypothesized effects between activity-travel chaining propensity and peak and off-peak motorized person miles traveled (PMT), using household travel survey data collected from four MPOs. The SEM framework also incorporates four mediator variables to explain the indirect effects of activity-travel chaining propensity on peak and off-peak motorized PMTs. Unlike the other studies, this study analyzes the direct effect of chaining different activity types on peak and off-peak motorized PMTs, which is an indicator of its contribution to the congestion level.

Land use, built environment, and transportation system characteristics have a considerable influence on activity-travel chaining frequency and patterns. Studies have found that high population density and land use mix at home locations are conducive to simple activity-travel chains and a higher share of transit as the primary activity-travel chain mode (Ahmed & Hyland, 2022; Chowdhury & Scott, 2020). These relationships measure a 'total' effect of land use variables on activity-travel chaining, without capturing the intricacies of the relationship through 'indirect' effects of other important factors, such as trip complexity and activity space characteristics. Results from these indirect effects can inform policymakers with more information on factors that can boost or hinder the attainment of desired goals.

The main contributions of the study are as follows:

- I quantify the impact of workers' and non-workers' activity-travel chaining behavior on cumulative travel = during the peak and off-peak, measured by peak and off-peak motorized PMT.
- I evaluate the impact of land use and built environment factors on PMT, considering direct and critical indirect effects.

4.2 Literature Review

Since the concept of activity-travel chaining incorporates improving trip making efficiency, studies have investigated the effect of activity-travel chaining on travel time savings (Huang & Levinson, 2017; Recker et al., 2001). Huang and Levinson (2017) calculates the travel time savings ratio by comparing the total travel time of two trips in a chain to the total travel times of the two unchained home-based trips. Their analysis shows that the travel time savings ratio positively influences the decision to include a destination in an activity-travel chain. My study uses this metric as an endogenous mediator to model between activity-travel chaining propensity and person miles traveled.

Other effects of activity-travel chaining include mode choice and vehicle miles traveled (VMT). Generally, studies find that activity-travel chaining encourages car usage as this mode provides the maximum flexibility in planning activity-travel chain paths (Huang & Levinson, 2017; Ye et al., 2007). Moreover, car has the potential benefits when hauling cargo or heavy shopping bags between trips. But studies comparing activity-travel chains in areas with different densities and traffic conditions revealed that public transit is often the mode of choice in activity-travel chains in high density areas with restricted parking availabilities (Currie & Delbosc, 2011a). Activity-travel chains can directly influence VMT along with indirectly influencing distances through mode choice. But there are only a handful of studies that investigated the direct impact of activity-travel chaining on VMT. Among these studies, Duncan (2016) finds that activity-travel chain reduces VMT, whereas, Kim et al. (1994) suggests that activity-travel chaining can increase VMT as multi-destination routes do not necessarily follow the shortest path. But none of their studies considered total VMT and analyzed VMT of activity-travel chains separately from the unchained trips. This study investigates the impact of chaining different activity types on average daily motorized PMT using a dataset containing all the trips (chained and unchained) carried out by each person. Moreover, the motorized PMT is expressed by peak and off-peak periods to capture the effect of activity-travel chaining in these periods.

By linking a specific group of trips with multiple destinations, an activity-travel chain can shape a person's activity space. Since the attributes of activity space is known to impact mode choice it can also affect the relationship between activity-travel chaining propensity and PMT. Moreover, larger activity space can encourage more trips with longer distances since the trip maker has more activity locations that fall within the vicinity of their route. Although there are multiple studies on the relationship between activity space and mode choice, to the best of my knowledge, only one study, by Concas and DeSalvo (2014), directly investigates the relationship between activity-travel chaining and activity space. They find that larger activity space is a result of increased number of chained trips, which in turn encourages automobile usage.

Considering the prevalence of work-based activity-travel chains, a large body of activity-travel chain literature includes analysis of activity-travel chains made by commuters (Bautista-Hernández, 2020; Rafiq & McNally, 2022b; Schneider, Daamen, et al., 2021; Wang, 2015b). Since commuters have a restricted time schedule and usually travel to a specific location on a regular basis, it is more convenient for them to add stops to the fixed commute trips. But non-workers have a relatively less restricted schedule and therefore have more flexibility in scheduling trips and routes, resulting in different activity-travel chaining characteristics compared to workers (Antipova & Wang, 2010; Chowdhury & Scott, 2020; Daisy et al., 2018). Motivated by these differences, this study also models the activity-travel chaining effects of workers and non-workers separately.

Location characteristics, like population density, land use diversity and transit availability are key determinants of activity-travel chaining. High population density and land use diversity at home location discourages complex activity-travel chaining, and vice versa (Chowdhury & Scott, 2020). Availability of transit near residence also decreases activity-travel chaining propensity, but mainly for non-work-based trips (J. Lee, 2016).

The translation of activity-travel chaining propensities to travel demand, such as PMT involves understanding the relationship between several important factors like, activity-travel chaining, mode choice, activity space travel time savings and PMT, as discussed in the literature above. But none of these studies analyzes the interdependencies among these factors. Only one study by Concas and DeSalvo (2014) includes both activity space and activity-travel chaining along with transit demand, residential location and population density. This study estimates all the direct and indirect effects between the activity-travel chaining, PMT, and location characteristics through path analysis in SEM. The quantification of activity-travel chains' effect on PMT is an important indication on the level of congestion it adds to the existing road networks. Moreover, the incorporation of location characteristics and mediator variables helps to identify the paths through which the effect on PMT is strongest and where policy intervention can be most effective to manage travel demand.

4.3 Data

This section provides an overview of the data and the modeling framework used in this study.

4.3.1 Overview of Data

This study uses activity-travel data for working and non-working population, extracted from the 2018-2019 Household Travel Survey of four MPOs in the United States. These MPOs are the Chicago Metropolitan Agency for Planning (CMAP), Puget Sound Regional Council (PSRC), Sacramento Area Council of Governments (SACOG), and Whatcom Council of Governments (WCOG). These MPOs provided trip-level activity-travel data along with the socio-economic characteristics of the households and persons. Among these MPOs, PSRC has the largest geographic area (6,384 sq. miles) and WCOG has the smallest (59 sq. miles.) (United States Department of Transportation, 2022). After filtering out the outliers and unreasonable values, the final dataset contains 10,394 persons, of which 7,416 are workers and 2,978 are nonworkers.

4.3.2 Descriptive Statistics

Table 4 provides the distribution of the variables considered in the conceptual model. For each MPO and 'Total' column, the values indicate percentage distributions for socio-economic characteristics and arithmetic means for the location and activity-travel characteristics.

Regarding household characteristics, household type has similar distribution across the MPOs with an overall high representation of persons from multi-member households without kids. On the contrary, the distribution of household income can be divided into two groups. CMAP and PSRC have the highest representation of high-income groups, while SACOG and WCOG have the highest representation of low-income groups. Except PSRC, all three other MPOs have a high (over 68%) proportion of person from households with one or more cars per licensed driver. PSRC has the highest percentage of persons with less than one household vehicles to license ratio.

Table 4: Distribution of Selected Variables Across Four MPOs

Variables	MPO				Total
	CMAP	PSRC	SACOG	WCOG	
Socio-economic Characteristics					
Household type					
Single-member	15.63	25.46	22.06	18.54	23.32
Multi-member without kids	50.00	53.98	52.27	54.39	53.34
Multi-member with kids (0-15 years)	34.38	20.56	25.67	27.07	23.34
Household income					
<$50K	18.75	20.37	25.21	34.80	23.65
$50-$100K	39.06	28.78	35.15	37.64	32.21
$100K or more	42.19	50.85	39.64	27.56	44.14
Household vehicle per license (1+)	68.23	53.79	82.64	85.04	67.83
Gender (Female)	53.65	50.66	56.70	55.85	53.45
Age (55 years +)	31.25	24.21	37.86	44.23	31.42
Student status (Yes)	16.15	8.47	9.31	6.18	8.66
Ethnicity/Race (Non-Hispanic Black)	6.25	2.45	3.17	0.41	2.55
Education (Graduate degree or above)	27.60	75.18	25.45	24.63	50.95
Employment status (Yes)	81.25	78.03	65.77	61.22	71.84
Work schedule (Full time)	55.73	68.15	54.75	40.33	60.08
Work location (Work from home only)	11.46	5.24	4.17	5.77	5.02
Location Characteristics					
Population density at home tract (persons/acre)	20.79	23.37	10.03	4.96	15.67
Land use mix at home tract	0.57	0.64	0.54	0.68	0.60
Land use mix at work tract	0.60	0.64	0.58	0.68	0.63
Transit frequency at home tract	13.98	79.60	6.43	0.00	44.87
Commute distance (miles)	12.11	9.24	12.67	9.82	7.18
Home-activity centroid distance (miles)	6.53	4.30	6.31	5.16	4.74
Activity-Travel Characteristics					
Subsistence chained	0.01	0.02	0.03	0.01	0.02
Maintenance chained	0.12	0.19	0.18	0.16	0.18
Discretionary chained	0.02	0.11	0.18	0.13	0.13
Travel time savings ratio	0.19	0.24	0.30	0.28	0.26
Total activity space area (sq. miles)	14.43	22.15	68.02	39.63	40.47
Average daily number of trips	3.56	4.34	4.92	4.90	4.60
NMT share	0.09	0.20	0.11	0.11	0.16
Transit share	0.09	0.13	0.02	0.01	0.08
Average daily peak motorized PMT (miles)	6.70	7.08	9.51	10.96	8.37
Average daily off-peak motorized PMT (miles)	13.60	10.89	17.42	9.76	13.16

Regarding person characteristics, Gender and Age have similar distributions across the MPOs. SACOG and WCOG have slightly higher proportions of females and age group 55 years and above than the other two MPOs. CMAP represents a considerably high proportion of students than other MPOs. Also, CMAP has the highest proportion of Non-Hispanic Black in contrast to WCOG, which has a very low proportion of respondents from this ethnic/racial background. The distribution of educational qualifications in CMAP, SACOG and WCOG shows a relatively low proportion of people holding 'graduate degree or above', whereas PSRC represents a considerably high proportion of people holding 'graduate degree or above'. Looking at the distribution of work-related variables, I see a relatively high proportion of employed persons in CMAP and PSRC compared to the other two MPOs. While the distribution of full-time workers is almost similar across the four MPOs, the proportion of workers who only 'work from home' is notably higher in CMAP.

Regarding the location characteristics, CMAP and PSRC have comparatively higher population densities than SACOG and WCOG, which constitute large rural areas. The land use mix at both home and work locations have a similar distribution across the MPOs, although PSRC and WCOG have slightly higher values. Like population density, transit frequency is also high in CMAP and PSRC, which can be directly attributed to the high population densities in these areas making transit operations feasible. Finally, both average commute distance and home-to-activity centroid distance are slightly higher for CMAP and SACOG. The correlation between these two variables is likely as there is a large proportion of workers in the sample and work location greatly influences locations of other activities.

Looking at the variables representing activity-travel characteristics, I see that the average values for the proportion of subsistence activities in activity-travel chains is low for all MPOs, while the proportion for maintenance activities is relatively high in PSRC and SACOG and the proportion of discretionary activities in activity-travel chains is higher in SACOG and WCOG. In relatively lower density areas like SACOG and WCOG, people need to travel longer distances to participate in their activities. On the other hand, higher density areas have closer proximity to activity locations, which can result in a lesser incentive to form frequent and long activity-travel chains. Therefore, it is more efficient to connect these trips into chains. The relatively high travel time savings ratio in SACOG and WCOG also supports the observed activity-travel chaining propensities suggesting low density areas encourage activity-travel chaining due to increased travel time savings. I investigate these relationships in detail in Sections 4.5 and 4.6 with the help of a structural equation modeling framework presented in Section 4.4. Among the three activity types, maintenance has the highest average share of trips (18%) in chains, followed by discretionary (13%) and subsistence (2%). The particularly large average activity space area of SACOG also corresponds to the high activity-travel chaining propensities of this MPO. When connecting multiple trips people are more likely to cover large area, which essentially increases their activity space compared to making only home-based trips. But the distribution of average daily trips shows no considerable variation across the MPOs, which may suggest that activity-travel chains are mainly substituting unchained trips.

As expected, the distribution of mode preference in both chained and unchained trips shows a low share of NMT and transit. Compared to the other three MPOs, PSRC represents a noticeably higher proportion of NMT, most likely for their vast network of transit service.

Finally, the average motorized peak and off-peak PMTs across MPOs vary. While the motorized peak PMT is highest in WCOG, off-peak PMT is noticeably high in SACOG compared to the other three MPOs. On average, people travel more in cars during the off-peak period (13 miles) than the peak period (8 miles).

4.4 Structural Equation Modeling Framework

Figure 4 illustrates the path diagram for the conceptual SEM framework, showing the hypothesized relationships between activity-travel chaining propensity, travel time savings ratio (TTSR), average daily trips, activity space area, mode share (proportion of NMT and transit trips), and motorized person miles travel (peak and off-peak), and the effects of the relevant exogenous variables. Chapter 2 provides detailed definition of the variables created for this study. The color of the arrows shows the hypothesized direction of direct effects—green means positive, and red means negative. I made the following considerations while developing the conceptual model.

- I hypothesize activity-travel chaining propensity has a positive effect on peak motorized PMT for workers and a negative effect on peak motorized PMT for non-workers. The commute trips of workers are more likely to include the activity-travel chains since these are regular and fixed trips occurring at peak hours. But non-workers with a relatively flexible time schedule can travel in off-peak hours avoid the most severe traffic congestion.
- I also hypothesize a positive effect of activity-travel chaining propensity on travel time savings ratio and activity space area. The reason behind this hypothesis is that the inclusion of more activities in a chain increases the travel distance between two anchor locations as the traveler has more destinations that are likely to deviate from the shortest path between the anchor locations. Moreover, the farther the activity

locations are from home, the more potential for travel time savings in forming activity-travel chains compared to separate home-based trips.

- I expect activity space area to positively affect travel time savings ratio, average daily trips and PMT, as larger activity space will include more potential activity locations, which will increase the opportunity to chain activities and encourage longer trip distances. On the contrary, activity space area will reduce the proportion of NMT and transit trips as larger areas promote longer trip distances which are makes NMT and transit less viable in many regions. In the same logic, I expect transit and NMT usage to reduce both peak and off-peak PMTs.
- Considering the potential correlation between some of the unobserved/unspecified variables, I include covariances of error terms for the proportions of NMT and transit trips, for the activity-travel chaining propensities, and for average daily number of trips and activity-travel chaining propensities.

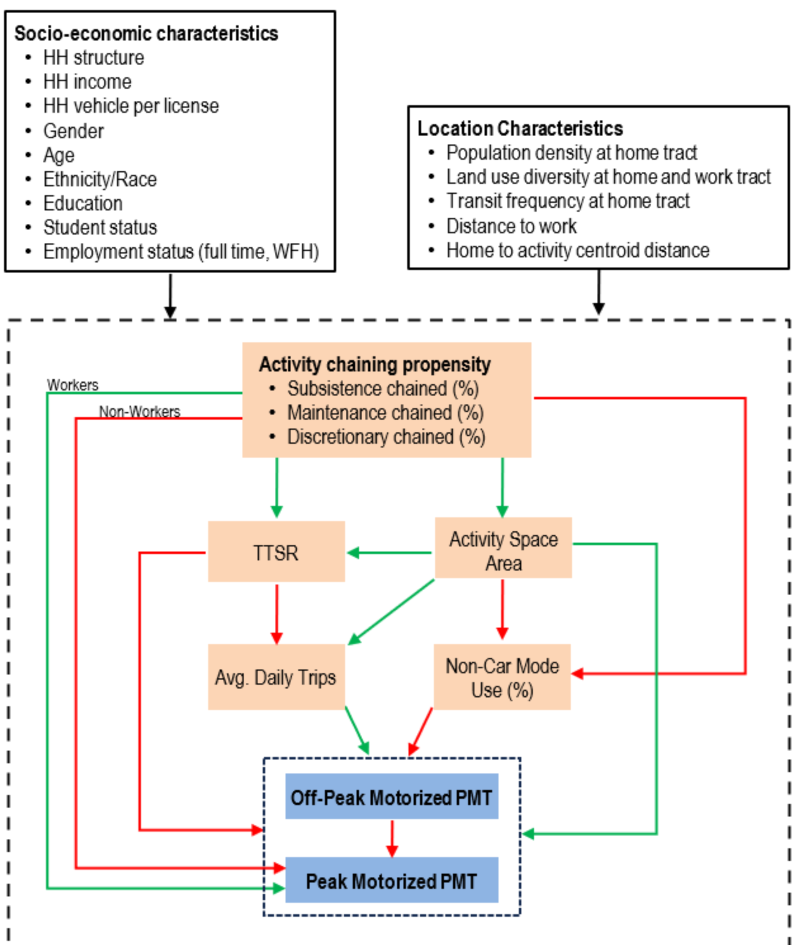


Figure 4: Conceptual Model Showing Hypothesized Relationships

As the conceptual model indicates, I expect activity-travel chaining behavior to result from interconnected relationships between a large number of factors. Hence, I use structural equation modeling (SEM) as it allows path analysis of multiple proposed relationships. SEM works by simultaneously estimating complex relationships through a set of linear equations comprising multiple endogenous and exogenous variables, where the variables can be observed or latent (Chavance et al., 2010).

This study uses a recursive version of SEM since there is no reciprocal effect or bi-directional relationship specified.

The following set of equations represent the mathematical formulation of SEM and portrays the specifications of as well as the interconnections among the 10 endogenous variables. Let us use $\boldsymbol{X}$ and $\boldsymbol{\Upsilon}$ to represent the vectors of observed exogenous and observed endogenous variables, respectively. Eq. 6 through Eq. 15 correspond to proportion of activity-travel chaining propensity of subsistence activities ($\boldsymbol{\Upsilon_S}$), activity-travel chaining propensity of maintenance activities ($\boldsymbol{\Upsilon_M}$), activity-travel chaining propensity of discretionary activities ($\boldsymbol{\Upsilon_D}$), travel time savings ratio ($\boldsymbol{\Upsilon_{TS}}$), activity space area ($\boldsymbol{\Upsilon_A}$), number of trips ($\boldsymbol{\Upsilon_{TR}}$), proportion of NMT trips ($\boldsymbol{\Upsilon_N}$), proportion of transit trips ($\boldsymbol{\Upsilon_T}$), peak motorized PMT ($\boldsymbol{\Upsilon_{PP}}$), and off-peak motorized PMT ($\boldsymbol{\Upsilon_{PO}}$).

$$\boldsymbol{\Upsilon_S} = \mathbf{B}_{\boldsymbol{S}}\boldsymbol{X} + \boldsymbol{\zeta_S} \tag{6}$$

$$\boldsymbol{\Upsilon_M} = \mathbf{B}_{\boldsymbol{M}}\boldsymbol{X} + \boldsymbol{\zeta_M} \tag{7}$$

$$\boldsymbol{\Upsilon_D} = \mathbf{B}_{\boldsymbol{D}}\boldsymbol{X} + \boldsymbol{\zeta_D} \tag{8}$$

$$\boldsymbol{\Upsilon_{TS}} = \mathbf{B}_{\boldsymbol{TS}}\boldsymbol{X} + \boldsymbol{Z_{TS}\Upsilon_S} + \boldsymbol{Z_{TS}\Upsilon_M} + \boldsymbol{Z_{TS}\Upsilon_D} + \boldsymbol{\zeta_{TS}} \tag{9}$$

$$\boldsymbol{\Upsilon_A} = \mathbf{B}_{\boldsymbol{A}}\boldsymbol{X} + \boldsymbol{Z_A\Upsilon_S} + \boldsymbol{Z_A\Upsilon_M} + \boldsymbol{Z_A\Upsilon_D} + \boldsymbol{\zeta_A} \tag{10}$$

$$\boldsymbol{\Upsilon_{TR}} = \mathbf{B}_{\boldsymbol{TR}}\boldsymbol{X} + \boldsymbol{Z_{TR}\Upsilon_{TS}} + \boldsymbol{Z_{TR}\Upsilon_{A}} + \boldsymbol{\zeta_{TR}} \tag{11}$$

$$\boldsymbol{\Upsilon_{N}} = \mathbf{B}_{\boldsymbol{N}}\boldsymbol{X} + \boldsymbol{Z_{N}\Upsilon_{A}} + \boldsymbol{Z_{N}\Upsilon_{S}} + \boldsymbol{Z_{N}\Upsilon_{M}} + \boldsymbol{Z_{N}\Upsilon_{D}} + \boldsymbol{\zeta_{N}} \tag{12}$$

$$\boldsymbol{\Upsilon_{T}} = \mathbf{B}_{\boldsymbol{T}}\boldsymbol{X} + \boldsymbol{Z_{T}\Upsilon_{A}} + \boldsymbol{Z_{T}\Upsilon_{S}} + \boldsymbol{Z_{T}\Upsilon_{M}} + \boldsymbol{Z_{T}\Upsilon_{D}} + \boldsymbol{\zeta_{T}} \tag{13}$$

$$\begin{aligned}\boldsymbol{\Upsilon_{PP}} = \mathbf{B}_{\boldsymbol{PP}}\boldsymbol{X} &+ \boldsymbol{Z_{PP}\Upsilon_{A}} + \boldsymbol{Z_{PP}\Upsilon_{S}} + \boldsymbol{Z_{PP}\Upsilon_{M}} + \boldsymbol{Z_{PP}\Upsilon_{TS}} + \boldsymbol{Z_{PP}\Upsilon_{A}} + \boldsymbol{Z_{PP}\Upsilon_{TR}} \\ &+ \boldsymbol{Z_{PP}\Upsilon_{N}} + \boldsymbol{Z_{PP}\Upsilon_{T}} + \boldsymbol{\zeta_{PP}}\end{aligned} \tag{14}$$

$$\begin{aligned}\boldsymbol{\Upsilon_{PO}} = \mathbf{B}_{\boldsymbol{PO}}\boldsymbol{X} &+ \boldsymbol{Z_{PO}\Upsilon_{A}} + \boldsymbol{Z_{PO}\Upsilon_{S}} + \boldsymbol{Z_{PO}\Upsilon_{M}} + \boldsymbol{Z_{PO}\Upsilon_{TS}} + \boldsymbol{Z_{PO}\Upsilon_{A}} + \boldsymbol{Z_{PO}\Upsilon_{TR}} \\ &+ \boldsymbol{Z_{PO}\Upsilon_{N}} + \boldsymbol{Z_{PO}\Upsilon_{T}} + \boldsymbol{Z_{PO}\Upsilon_{PP}} + \boldsymbol{\zeta_{PO}}\end{aligned} \tag{15}$$

where,

$\boldsymbol{\Upsilon}$ = vector of observed endogenous variables

$\boldsymbol{X}$ = vector of observed exogenous variables representing socio-economic and location characteristics

$\mathbf{B}$ = vector of coefficients for observed exogenous variables $\boldsymbol{X}$

$\boldsymbol{Z}$ = vector of coefficients for observed endogenous variables $\boldsymbol{\Upsilon}$

$\boldsymbol{\zeta}$ = vector of error terms for the observed endogenous variables

4.5 Model Estimation Results

The estimated SEM provided a satisfactory goodness-of-fit across all major criteria. Table 5 provides the goodness-of-fit values for the models with worker and non-worker samples. The values of root mean squared error approximate (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Index (TLI) are within the recommended thresholds for a satisfactory model fit – RMSEA ≤ 0.08, CFI ≥ 0.80 and TLI ≥0.80 (Acock, 2013; Kline, 2016). Moreover, both of my models exceed the good model fit thresholds indicated by RMSEA ≤ 0.06 and CFI ≥ 0.90 (Marsh et al., 2004; McDonald & Ho, 2002). Consequently, I can say that the hypothesized model is a reasonable representation of the underlying relationships in the data.

Table 5: Goodness-of-fit Statistics of the Two SEM Models

Goodness-of-fit Statistic	SEM with Worker Sample	SEM with Non-Worker Sample
Loglikelihood ratio (χ^2)	1359.489	430.336
Degrees of freedom	80	68
RMSEA	0.046	0.042
CFI	0.949	0.965
TLI	0.856	0.904

Table 6-8 presents the coefficient estimates from the SEM and each table contains results for both workers and non-workers. Table 6 presents the estimated direct effects on the five mediator variables, Table 7 presents estimated direct and total effects on the peak and off-peak motorized PMT and Table 8 presents the estimated direct effects of socio-economic and location variables on activity-travel chaining propensity.

4.5.1 Direct Effects in the Structural Part

Effects between Activity-Travel Chaining Propensity, PMT, and Mediator Variables

As expected, the addition of all three activity types (subsistence, maintenance and discretionary) in activity-travel chains positively affects travel time savings ratio for both workers and non-workers (Table 6). Comparing the standardized coefficients, the chaining of maintenance activities has greatest the effect on travel time savings ratio for both workers and non-workers, but the magnitude of the effect is noticeably higher for non-workers than workers.

The effect of activity-travel chaining propensity on peak and off-peak motorized PMTs differ by the activity type. An increase in chaining propensity of subsistence activities increases off-peak motorized for workers and peak motorized PMT for non-workers. The addition of maintenance activities in chains decreases peak motorized PMT for both workers and non-workers and decreases off-peak motorized PMT for non-workers. (Table 7). Moreover, chaining more discretionary activities increases peak motorized PMT for non-workers and off-peak PMT for both workers and non-workers. These findings indicate that the effects of activity-travel chaining on peak motorized PMT vary by activity type and potential substitution of trips for maintenance activities in peak hours with trips for chained maintenance activities in off-peak hours.

The effects of activity-travel chaining propensity on mode share are interesting. Workers who include more of their subsistence and discretionary activities in chains have higher NMT usage but lower transit usage (Table 6). Conversely, non-workers have higher NMT usage when they have more chained subsistence and discretionary activities but have lower transit usage when chaining more discretionary activities. And chaining more maintenance activities is negatively associated with NMT and transit usage for both workers and non-workers.

I also find that the travel time savings ratio positively affects total trips for both workers and non-workers but positively affects peak and off-peak motorized PMT for only workers (Table 6-7). This finding indicates that people potentially use the travel time saved from activity-travel chaining to travel more in off-peak hours. The positive relationship between peak PMT and travel time savings ratio for workers is most likely due to the prevalence of work-based activity-travel chains, which mostly occurs in peak hours.

Also as hypothesized in the conceptual model, I find a positive effect of activity space area on motorized PMT for both workers and non-worker but a negative effect on transit usage for workers (Table 6-7), which corresponds to the findings by Harding et al. (2022).

Table 6: Estimated Direct Effects on the Five Mediator Variables in Worker and Non-Worker Groups

Outcome Variables	Worker					Non-Worker				
	Travel Time Savings Ratio	Activity Space Area	Average Daily Trips	NMT Share	Transit Share	Travel Time Savings Ratio	Activity Space Area	Average Daily Trips	NMT Share	Transit Share
Predictors										
Socio-economic Characteristics										
Household type (base: Single member)										
Multi-member without kids	---	---	0.097	-0.065***	-0.036***	---	---	0.006	-0.025**	-0.043***
Multi-member with kids (0-15 years)	---	---	0.780***	-0.101***	-0.081***	---	---	1.069***	-0.084***	-0.085***
Household income (base: < $50K)										
$50-$100K	---	---	0.063	0.010	-0.013*	---	---	0.097	-0.015	-0.040***
$100K or more	---	---	-0.0005	0.010	-0.007	---	---	0.388***	-0.023**	-0.045***
Household Vehicle per license (1+)	---	0.134***	0.212***	-0.105***	-0.103***	---	0.069***	0.196**	-0.093***	-0.102***
Gender (Female)	---	---	0.068	-0.023***	0.0007	---	---	0.039	-0.005	-0.011*
Age (55 years +)	---	---	0.006	-0.039***	-0.019***	---	---	-0.068	-0.057***	-0.044***
Ethnicity/Race (Non-Hispanic Black)	---	---	---	-0.026	0.045***	---	---	---	-0.070**	0.068***
Education (Graduate degree or above)	---	---	---	0.051***	0.037***	---	---	---	0.051***	-0.008
Work schedule (Full time)	---	0.076***	-0.238***	---	---	---	---	---	---	---
Work location (Work from home only)	---	-0.057*	0.169**	0.031***	-0.048***	---	---	---	---	---
Location Characteristics										
Population density at home tract (100 persons/acre)	0.007	-0.166***	-0.210	0.339***	0.093***	0.007	-0.184**	0.261	0.518***	0.120***
Land use mix at home tract	-0.019	-0.243***	0.105	0.035*	0.018	-0.021	-0.209***	-0.064	0.023	0.052**
Land use mix at work tract	---	-0.072**	-0.160	0.015	0.100***	---	---	---	---	---
Transit frequency at home tract	---	---	---	---	0.015***	---	---	---	---	0.019***
Commute distance (miles)	---	0.003***	-0.002	-0.002***	0.0004*	---	---	---	---	---
Home-activity centroid distance (miles)	---	0.047***	-0.048***	---	---	---	0.039***	-0.033***	---	---
Activity-Travel Characteristics										
Subsistence Chained	0.094***	0.131***	---	0.028**	-0.020*	0.110***	0.095*	---	0.078***	0.012
Maintenance Chained	0.180***	0.207***	---	-0.043***	-0.061***	0.268***	0.193***	---	-0.027**	-0.025**
Discretionary Chained	0.119***	0.286***	---	0.039***	-0.031***	0.099***	0.185***	---	0.028***	-0.028***
Travel Time Savings Ratio	---	---	3.810***	---	---	---	---	2.390***	---	---
Activity Space Area (100 sq. miles)	0.034***	---	0.230***	-0.001	-0.006*	0.035***	---	0.253***	-0.008	-0.0008

Note: Sig. codes: '***' 0.01 '**' 0.05 '*' 0.10

Table 7: Estimated Direct and Total Effects on the Peak and Off-Peak Motorized PMT in Worker and Non-Worker Groups

Outcome Variables	Direct Effects				Total Effects			
	Worker		Non-Worker		Worker		Non-Worker	
	Peak PMT	Off-Peak PMT	Peak PMT	Off-Peak PMT	Peak PMT	Off-Peak PMT	Peak PMT	Off-Peak PMT
Predictors								
Socio-economic Characteristics								
Household type (base: Single member)								
Multi-member without kids	---	---	---	---	0.171***	0.179***	0.066***	0.116***
Multi-member with kids (0-15 years)	---	---	---	---	0.429***	0.496***	0.372***	0.478***
Household income (base: < $50K)								
$50-$100K	0.094***	0.006	0.031	0.041	0.103***	-0.011	0.119**	0.183***
$100K or more	0.203***	0.024	0.092**	0.075**	0.196***	-0.040	0.242***	0.274***
Household Vehicle per license (1+)	0.051**	0.077***	0.064	0.068*	0.480***	0.537***	0.348***	0.501***
Gender (Female)	0.043**	-0.039**	-0.037	-0.002	0.118***	0.042	-0.006	0.083**
Age (55 years +)	-0.138***	0.059**	-0.101**	0.112***	-0.029	0.214***	0.008	0.341***
Student Status (Yes)	---	---	---	---	0.009	0.036***	0.034	-0.017
Ethnicity/Race (Non-Hispanic Black)	---	---	---	---	-0.037	-0.036	0.007	-0.007
Education (Graduate degree or above)	---	---	---	---	-0.160***	-0.173***	-0.051***	-0.078***
Work schedule (Full time)	0.126***	---	---	---	0.105***	-0.077***	---	---
Work location (Work from home only)	-0.288***	-0.143***	---	---	-0.215***	0.029	---	---
Location Characteristics								
Population density at home tract (100 persons/acre)	-0.097***	0.099	-0.644***	-0.263**	-0.999***	-0.906***	-1.463***	-1.504***
Land use mix at home tract	---	---	---	---	-0.155****	-0.177***	-0.198***	-0.279**
Land use mix at work tract	---	---	---	---	-0.299***	-0.357***	---	---
Transit frequency at home tract	---	---	---	---	-0.029***	-0.030***	-0.022***	-0.040***
Commute distance (miles)	0.012***	0.028***	---	---	0.017***	0.029***	---	---
Home-activity centroid distance (miles)	---	---	---	---	0.004***	0.004***	0.007***	0.011***
Activity-Travel Characteristics								
Subsistence Chained	-0.014	0.204***	0.182**	0.023	0.072	0.285***	0.155	-0.077
Maintenance Chained	-0.081**	-0.018	-0.203***	0.108**	0.288***	0.327***	0.043	0.448***
Discretionary Chained	0.030	0.160***	0.126***	0.068*	0.168***	0.283***	0.229***	0.182***
Travel Time Savings Ratio	0.352***	0.126**	0.070	0.162	0.758***	0.621***	0.456***	0.496***
Activity Space Area (100 sq. miles)	0.141***	0.217***	0.258***	0.374***	0.206***	0.251***	0.325***	0.413***
Average Daily trips	0.106***	0.184***	0.161***	0.162***	0.106***	0.155***	0.161***	0.142***
NMT Share	-1.765***	-2.426***	-1.209***	-2.021***	-1.765***	-1.946***	-1.209***	-1.874***
Transit Share	-1.856***	-2.452***	-1.134***	-2.168***	-1.856***	-1.948***	-1.134***	-2.030***
Peak PMT	---	-0.271***	---	-0.121***	---	-0.271***	---	-0.121***

Note: Sig. codes: '***' 0.01 '**' 0.05 '*' 0.10

Effects of Exogenous Variables

Overall, I find that the impact of socio-demographic and location characteristics on activity-travel chaining propensity, travel time savings ratio, average daily trips, activity space and mode share and PMT are consistent with prior findings in the literature (Table 6-8). Overall, the significances vary between the two groups, but the signs are consistent between workers and non-workers with few exceptions. I will discuss notable findings and the differences in effects between worker and non-worker groups. One noticeable difference in the coefficients is the impact of gender as results show that female workers have higher peak motorized PMT and lower off-peak motorized PMT than male workers, whereas these effects are not significant for non-workers. Also, females have a positive activity-travel chaining propensity for all activity types, except subsistence for workers.

Table 8: Estimated Direct Effects on the Activity-Travel Chaining Propensity in Worker and Non-Worker Groups

Outcome Variables	Worker			Non-Worker		
	Subsistence Chained	Maintenance Chained	Discretionary Chained	Subsistence Chained	Maintenance Chained	Discretionary Chained
Predictors						
Socio-economic Characteristics						
Household type (base: Single member)						
Multi-member without kids	-0.005	-0.040***	-0.062***	-0.006	-0.026	-0.046**
Multi-member with kids (0-15 years)	0.002	0.069***	0.029*	0.022	-0.003	-0.010
Household income (base: <$50K)						
$50-$100K	-0.012	-0.022*	0.018	-0.007	0.034*	0.031
$100K or more	-0.007	-0.012	0.010	-0.005	0.027	0.029
Gender (Female)	0.005	0.075***	0.032***	0.014*	0.073***	0.055***
Age (55 years and above)	0.009	0.023**	-0.032**	-0.010	0.061***	0.001
Student Status (Yes)	0.129***	---	---	0.224***	---	---
Work schedule (Full time)	-0.056***	-0.018	-0.008	---	---	---
Work location (Work from home only)	0.032***	0.090***	0.019	---	---	---
Location Characteristics						
Population density at home tract (100 persons/acre)	-0.033**	-0.147***	-0.196***	-0.042	-0.108*	-0.127**
Land use mix at home tract	-0.023	0.022	0.061*	-0.050**	-0.036	-0.056
Land use mix at work tract	-0.059***	-0.098***	-0.122***	---	---	---

Note: Sig. codes: '***' 0.01 '**' 0.05 '*' 0.10

Another difference in the effects of socio-demographic variables concerns the household structure. Workers from households with children between 0-15 years olds have a positive tendency towards chaining maintenance and discretionary activities, whereas non-workers in the same household type have no significant effects toward chaining these activities (Table 8). The effect of households without children on activity-travel chaining propensity of maintenance activities are negative for workers. Households with children have more demand for maintenance activities like grocery and shopping. Workers in these households are more likely to add these activities to their commute trips as it avoids making additional home-based trips, which saves time in their restricted schedule.

Like existing literature, this study finds significant effect of population density and land use mix on activity-travel chaining propensity (Chowdhury & Scott, 2020). Workers and non-workers residing in densely populated areas have a lower propensity for chaining maintenance and discretionary activities. Higher land use mix at home location increases chaining of discretionary activities for workers and decreases chaining of subsistence activities for non-worker. Higher land use mix at work location decreases chaining of maintenance and discretionary activities. As expected, increased population density and land use mix decreases activity space area, peak and off-peak motorized PMT, and increases NMT and transit mode share over auto.

4.5.2 Indirect and Total Effects in the Structural Part

As Figure 4 portrays, there are several indirect effects of activity-travel chaining propensity on peak and off-peak motorized PMT through travel time savings ratio, activity space area, average daily trips, and mode share. The total effect between a predictor and a dependent variable is the sum of the direct effect and the product of the indirect effects between these variables. Eq. 16 and 17 summarize the calculation of indirect and direct effects, respectively.

$$IE_{i,k} = DE_{i.j} \cdot DE_{j,k} \tag{16}$$

$$TE_{i,k} = DE_{i.k} + IE_{i,k} \tag{17}$$

Suppose I need to calculate the total effect of variable i on variable k. These two variables have mediator variable *j*, that mediates the effect of variable *i* on variable *k*. $DE_{i.k}$ represents direct effect between variable *i* and variable *j*. $DE_{i.j}$ and $DE_{j,k}$ represents the direct effects of *i* on the *j* and the direct effect of *j* on *k*, respectively. Therefore, the indirect effect between *i* and k ($IE_{i,k}$) is the product of the two direct effects as represented in Eq. 16. And the total effect between *i* and *k* ($TE_{i,k}$) is the sum of the direct and indirect effects (Eq. 17).

From the calculated total effects, I see that the activity-travel chaining of subsistence and maintenance activities has a positive effect on peak motorized PMT of workers and activity-travel chaining of discretionary activities has a positive effect on peak motorized PMT of both workers and non-workers. Considering the presence of negative direct effects of chaining maintenance activities on peak PMT, the positive total effect is due to the strong positive mediation effect of travel time savings ratio, activity space area and average daily trips. The strongest mediation effect comes through the positive effect of average daily trips, followed by size of activity space. The only negative impact of activity-travel chaining propensity on peak and off-peak PMT is through mode share. People who use NMT and transit more frequently than auto have less peak and off-peak PMT. Also, the chaining of subsistence and discretionary activities increases NMT usage for both workers and non-workers. This finding, along with the positive total effects of population density and land use mix on NMT and transit mode share, and negative total effects on activity space provides useful guidelines for policies aiming to reduce PMT. As these results show, bringing a diverse range of activities near residential areas reduces activity space and encourages NMT and transit usage, which in turn reduces the motorized PMT. While this finding (land use diversity decreases PMT) is consistent with prior research, my modeling framework provides additional detail into the complex interrelationships between important activity-travel behaviors underlying the finding.

4.6 Discussion and Policy Implications

This study has several notable findings. First, I find that activity-travel chaining among non-workers also has a positive impact on the peak PMT, like workers. The estimated total effects indicate that activity-travel chaining of maintenance and discretionary activities two of the largest contributors to peak PMT for workers and non-workers. I also see negative direct effects of chaining maintenance activities on peak PMT of workers and non-workers, providing evidence of possible substitution of activities related to shopping, dining, healthcare, etc., during the peak hour with the same or similar activities in chains formed during the off-peak hour. Hence, policies to manage peak-hour travel demand need to consider non-working population as well as the working population and their activity-travel chaining propensities to properly evaluate the level of traffic congestion. Since chaining of maintenance activities, like shopping and dining has the significant negative direct effect, the siting of these activities plays an important role in managing peak PMT.

I also find that activity-travel chaining propensities of subsistence and discretionary activities have positive effects on the proportion of NMT trips. Since, the use of NMT has the largest significant negative effect on peak PMT, transportation and land use planners can leverage this relationship to reduce peak PMT by providing adequate walking and biking facilities near major activity centers and improve NMT connectivity between residential areas and activity centers.

The analysis also indicates important differences between the socio-economic and location characteristics of the workers and non-workers that affect their activity-travel chaining propensities and impact on PMT. I find positive effects of female and households with children between 0-15 years on chaining maintenance and discretionary activities and peak motorized PMT in the worker group. While in case of non-worker group, the relationships are similar, except for the insignificant effects of female and household with children on peak motorized PMT. Except for the insignificant effects, these results coincide with the findings of Antipova and Wang (2010), who observe that worker females have a higher tendency to chain activities than males, especially when they have children in the household. As existing literature suggests, females from households with children makes more chained trips than men as females tend to take more responsibility of household and childcare (Kumar & Levinson, 1995; McGuckin & Murakami, 1999).

The findings from the effects of location characteristics are supported by existing literature and useful for policy formulation. Higher population density reduces the activity-travel chaining propensity of workers and non-workers. Higher land use mix at work location reduces activity-travel chaining propensities of workers, whereas higher land use mix at home location has no significant effect on activity-travel chaining propensities of non-workers, except for subsistence activities. From this finding, it appears that non-workers chains activities mainly by choice, not due to the characteristics of the built environment. Therefore, land use policies to reduce peak PMT might not be effective for non-workers as workers.

4.7 Conclusions

The goal of this study is to analyze the effect of activity-travel chaining propensity on peak and off-peak motorized PMT. Along with the socio-demographic and location characteristics, the methodology incorporates four mediating variables (i.e., travel time savings ratio, activity space area, average daily trips and mode share) to capture the indirect effects of activity-travel chaining propensity on the average daily peak and off-peak motorized PMT. I use the 2018-2019 household travel survey dataset of four MPOs (CMAP, PSRC, SACOG and WCOG) and analyze the data with the help of structural equation modeling techniques. The study builds separate models for workers and non-workers to contrast the relationships.

The results provide some new insights on activity-travel chaining behavior and its impact for both worker and non-worker groups. This study finds positive and strong impact of activity-travel chaining propensities of worker and non-worker on peak-hour motorized PMT. Moreover, off-peak hour chaining of maintenance activities by workers non-workers appears to be substituting these activities in the peak hours. I also find significant indirect effects of activity-travel chaining propensities through the mediator variables, which provide opportunities to manage peak PMT. In particular, leveraging the positive association between NMT usage and subsistence and discretionary activity-travel chains can help mitigate PMT during congested periods by improving walking and biking facilities near residences and major activity centers. The coefficient estimates for the socio-economic and location characteristics also distinguish activity-travel chaining behavior and its impact between workers and non-workers.

This study has two main limitations. First, workers have some important predictors (e.g., commute distance, work location attributes) for analyzing their travel behavior that are not applicable for non-workers. Due to this difference in variable specification, it is not possible to estimate a multi-group SEM to compare the relationships directly between the worker and non-worker groups. Second, the study could not identify the joint trips between household members, especially those occurring with workers and non-workers in the same trip. Investigating these joint trips could provide more explanation on the peak PMTs of non-workers.

CHAPTER 5: EXPLORING THE ROLE OF RIDE-HAILING IN ACTIVITY-TRAVEL CHAINS

5.1 Introduction

An *activity-travel chain* is a series of trips taken in which the starting and ending trips in the chain succeed and precede, respectively, a specific activity type (e.g., home and/or work) or an activity with a duration greater than some time threshold (e.g., thirty minutes or four hours). Research suggests travelers have a propensity to form activity-travel chains to reduce travel costs and/or save time (Liu, 2012; Strathman et al., 1994a; Wang, 2015b), such as when travelers stop at non-work activity locations when traveling to or from work. In chaining activities, travelers are potentially decreasing overall vehicle miles traveled (VMT) and positively impacting the transportation system of a region (Carlson & Howard, 2010; Duncan, 2016).

The private automobile (i.e. auto) offers many advantages to travelers who chain their trips on a regular basis, including flexibility in scheduling and selection of routes, as well as overall travel comfort and the ability to store items between trips (Xianyu, 2013). However, researchers also find that in areas with high transit demand, travelers complete complex activity-travel chains using rail-based transit services in order to avoid roadway congestion and parking costs (Currie & Delbosc, 2011a).

The recent emergence and proliferation of ride-hailing companies like Uber and Lyft offers travelers another modal option to complete activity-travel chains or portions of activity-travel chains. In general, ride-hailing services provide many of the benefits of a private auto without the high upfront purchasing costs nor parking costs. In contrast to transit, ride-hailing services obviate the first/last mile problem by providing transportation directly from one activity location to the next. Ride-hailing trips are also a lot more flexible than transit trips in terms of scheduling and routing. Hence, ride-hailing includes most of the benefits and avoids most of the pitfalls of both personal vehicles and transit for activity-travel chaining purposes. However, a notable downside of ride-hailing (and transit and walking) relative to a personal vehicle is the inability to store items inside a vehicle between trips. Another downside of ride-hailing is the relatively high cost per trip.

Given the potential of ride-hailing to be an attractive mode for activity-travel chaining, the goal of this study is to explore the role ride-hailing currently plays within activity-travel chains. The study focuses on understanding the attributes of the travelers who use ride-hailing within activity-travel chains, the activities and trips within activity-travel chains with ride-hailing, the complexity and structure of activity-travel chains made with ride-hailing, and the land-use characteristics of the areas where ride-hailing activity-travel chains typically occur. To meet the study's overarching goal and answer specific research questions, this chapter includes (i) a descriptive analysis of the characteristics of travelers across modes and across trip purposes or activities who activity-travel chain, (ii) a binary logit model to understand the modal, individual, land-use, activity, and activity-travel chain attributes correlated with the usage of ride-hailing within an activity-travel chain, and (iii) a nested logit model to capture the modal, individual, land-use, activity, and activity-travel chain attributes correlated with the choice of a primary activity-travel chain mode. The analysis employs data from the largest, by population, 50 core-based statistical areas (CBSAs), obtained from the 2017 National Household Travel Survey (NHTS) dataset.

While several existing studies attempt to reveal trip making patterns of ride-hailing users, as far as the authors are aware, this is the first study to explore ride-hailing within the context of activity-travel chains. Since activity-travel chaining is a relatively complex form of travel behavior with specific travel requirements, understanding the role ride-hailing plays within activity-travel chains should help transportation planners, policymakers, and system managers formulate policies to enable better integration of ride-hailing into people's daily travel routines, to ultimately improve mobility and accessibility. The literature also points to the significant opportunity for ride-hailing to support multi-modal travel (Shaheen & Chan, 2016), which is related to activity-travel chaining.

The remainder of the chapter is structured as follows. The next section reviews travel behavior-related ride-hailing and activity-travel chaining research. Sections 5.3 and 5.4 present the theoretical framework and modeling approach to meet the study's objectives. Section 5.5 provides an overview of the data used to answer the study's research questions. Section 5.6 presents the model results, while Section 5.7 discusses the model results and their broader implications. The final section concludes the study with a summary of the study, key findings, study limitations, and future research directions.

5.2 Literature Review

The impact of ride-hailing services on the mobility of trip makers has been quite apparent in the last few years. Their tremendous growth is evident in the nearly four-fold increase in the number of ride-hailing trips in New York City between November 2015 and November 2019 (TLC, 2020). Although the demand for ride-hailing services and the supply of ride-hailing drivers diminished greatly during the COVID-19 pandemic, this study implicitly assumes that ride-hailing services will once again play an important role in urban areas in the coming years.

Previous research indicates that ride-hailing services are mostly associated with people in the middle-income group and in households with low auto access (Feigon & Murphy, 2016a). The same study also found a high correlation between users of ride-hailing services and transit users. In a similar study that distinguishes between young adults and middle-aged adults in California when analyzing factors impacting the use of ride-hailing services, findings indicate that ride-hailing is highly popular among younger, Hispanic, and higher-educated persons (Alemi et al., 2018). The adoption of ride-hailing was also found to be higher when individuals are more likely to associate modern technology within their daily life, make long-distance trips, and often travel to the airports. Moreover, studies indicate a significant positive influence of built environment variables, such as automobile accessibility, land use mix, and residential density on the use of ride-hailing services (Alemi et al., 2018; Dias et al., 2017). Along with relieving the traveler from the hassle of parking their car, ride-hailing services are also popular when the traveler is unable to drive and because of the convenience in access and payment (Rayle et al., 2014).

There are mixed findings regarding the impact of ride-hailing services on transit. Some studies find evidence that the use of ride-hailing services increase the use of transit depending on the location and type of transit service (Circella & Alemi, 2018; Clewlow & Mishra, 2017). Conversely, a study found bus ridership declined by 12.7% since 2010, when the first ride-hailing service began operation (Graehler et al., 2018). The same study also shows that between 2015 and 2018 in New York, daily ride-hailing trips increased by

540,000 whilst transit trips reduced by 580,000 (Graehler et al., 2018). While studying the change in transit ridership pertaining to 20 U.S. cities, Sadowsky and Nelson (Sadowsky & Nelson, 2017) find that the introduction of ride-hailing services (Uber) had a complementary effect on the use of public transportation. But when the second company (Lyft) entered the market, they observed an opposite effect, represented by a reduction in the transit ridership to or below the level which existed before the introduction of ride-hailing services. Sadowsky and Nelson (Sadowsky & Nelson, 2017) speculate that the first entry of the ride-hailing services acted as a solution to the transit first-/last-mile problem, whereas the entry of the second company created price competition between ride-hailing companies, effectively decreasing ride-hailing prices, and subsequently making ride-hailing travel a substitute for transit. Another study comprising seven metropolitan areas in the U.S. estimated that 9% of transit trips were substituted by ride-hailing services (Clewlow & Mishra, 2017). Noting the potential substitution and complementary effects of ride-hailing on transit services, Circella et al. (Circella et al., 2018) assert that the substitution effect might significantly prevail over the complementary effect, if trip makers have low or zero access to a private automobile and frequently use Uber or Lyft in combination with other modes.

Another research question pertaining to ride-hailing services is their impact on auto use and ownership since ride-hailing services provide most of the benefits of a private automobile. In San Francisco, Rayle et al. (2016) conducted intercept surveys of 380 ride-hailing users and compared the surveys with data from: the American Community Survey (ACS), a previous taxi users survey, and GPS trip records of a taxi company. Their findings indicate that 38% of ride-hailing users who own a car, drove less frequently (up to twice per week) after the introduction of ride-hailing. However, the researchers could not find any significant reduction in auto ownership among ride-hailing users. With a broader study area, covering seven metropolitan areas in the U.S., Clewlow and Mishra (2017) conducted an internet-based survey to understand the factors influencing the use of ride-hailing services. A small proportion, 9%, of the respondents reported a reduction of at least one vehicle in their households when they opted for ride-hailing services. But what these studies could not establish is whether there is any net increase in the vehicle miles traveled (VMT), which is an important metric associated with congestion, energy consumption, and vehicle emissions. Clewlow and Mishra (2017) emphasize the importance of induced VMT (i.e., by non-drivers and non-auto owners) and dead-heading VMT (i.e., VMT generated by empty ride-hailing vehicles) in their evaluation. In an effort to shed light on this issue, Henao and Marshall (2019) estimate the impact of ride-hailing on system-wide VMT through a quasi-natural experiment, where the first author drove for Uber and Lyft to obtain trip and passenger data. Results indicate that ride-hailing services increase VMT by 83.5% compared to other modes, a significant portion (40.8%) of which is attributed to the dead-heading VMT. Also, 13% of the respondents in Henao and Marshall (2019) mentioned that they are substituting ride-hailing services for auto ownership.

The findings in the prior paragraphs suggest a significant change in travel patterns and behavior due to the introduction of ride-hailing services. As established by numerous studies in the past several decades, activity-travel chaining is an important component of travel behavior. Moreover, activity-travel chaining has a direct effect on the way people plan their daily trips and activities. People link or chain their trips together when they have a restriction on the time and/or the day they can travel. Activity-travel chaining can also arise simply because it is more convenient. For example, when the preferred grocery store is located along or near a traveler's commute route, it is more efficient to add a stop when returning home from work rather than making a separate trip to the grocery store from home. Evidence suggests that travelers have a propensity to form activity-travel chains, by adding non-work trips to work trips, with the aim to save travel cost and time (Strathman et al., 1994b).

Considering activity-travel chaining's impact on mode choice and the spatial and temporal distribution of trips, research has attempted to utilize activity-travel chaining characteristics to improve travel demand forecasts (Abdelghany et al., 2001; Goulias & Kitamura, 1991; Krygsman et al., 2007). Trip makers were found to choose modes differently when they are making a chain of trips compared to a single direct trip. Studies also show that along with the decision to activity-travel chain, the activity-travel chain's level of complexity (number of stops, cumulative activity duration, etc.) influences the primary and/or secondary modes. In highly complex activity-travel chains, private auto is often the most preferred mode as it allows flexibility in scheduling and impromptu changes in the number and sequence of trips (Dong et al., 2006; M. S. Lee & McNally, 2003). Another study by McGuckin et al. (2005), using the 2001 National Household Travel Survey dataset, reports a higher tendency to use personal vehicles when activity-travel chains are made to and from work compared to a single activity-travel chain in either commute direction. But there are cases, such as in a study conducted in Melbourne, where complex activity-travel chains were highly correlated with transit (rail and tram) rather than personal cars (Currie & Delbosc, 2011b). Although the auto is known to provide the most flexibility, the activity-travel chain makers in the Melbourne study choose transit for activity-travel chaining to avoid roadway congestion and parking.

As mentioned previously, despite sizable and growing bodies of research analyzing (i) demand for ride-hailing, (ii) travel behavior related to ride-hailing in general, and (iii) activity-travel chaining behavior in general, the authors are unaware of any other study that examines the relationship between ride-hailing and trip-chaining. Hence, this study aims to fill this gap in the literature by providing behavioral insights into the role ride-hailing currently plays within activity-travel chains.

5.3 Theoretical Framework

Before delving into the theoretical framework underlying this study, it is important to note that this study assumes that a traveler chooses to chain a series of activities and trips prior to making mode choice decisions. While it is possible that the decision to chain activities is made simultaneously with mode choice, or that mode choice decisions are made prior to the decision to chain activities in some cases, a key study in the literature finds that the attributes of activity-travel chains better explain mode choice, than vice versa (Ye et al., 2007).

5.3.1 Operational Definitions

The current study uses data from the 2017 NHTS (FHWA, 2017) to determine the role ride-hailing currently plays within activity-travel chains. While the NHTS dataset contains a file for activity-travel chains, the current study does not use the NHTS activity-travel chain dataset. The NHTS constructs its activity-travel chain dataset in such a manner that home and work activities anchor every activity-travel chain. Conversely, the current study constructs its activity-travel chain dataset based on activity duration, i.e., every activity-travel chain is anchored by activities lasting longer than four hours and the anchor points are independent of activity type. In contrast to the previous two chapters, this definition does not require home and work activity locations to be anchors by default. Chapter 2 includes both of these definitions along with the definitions of primary activity, secondary activity, primary mode, and secondary mode of an activity-travel chain. All of these definitions are important for this chapter.

The activity-travel chain definition used in this study allows home and work activities to be treated as any other activity. If their durations are less than four hours, home and work activities are classified as intermediary trip activities, rather than automatically being a terminating activity for an activity-travel chain. In the context of activity-travel chaining, there are certainly cases in which trips ending at home locations should be considered a secondary activity, e.g., when a person needs to drop his children or perishable groceries at his home before going to another, more important (or at least time-consuming) activity.

For clarification, please note that a single trip represents travel between two activity locations. The trip can be unimodal or multimodal, where in the latter case the traveler switches modes between activity locations. Moreover, even if all the individual trips within an activity-travel chain are unimodal, the activity-travel chain itself can be multimodal.

Figure 5 displays how the anchor activity duration cut-off impacts the construction of activity-travel chains. The figure shows that as the anchor activity duration cut-off increases from 60 minutes to 240 minutes, to 360 minutes the number of activity-travel chains decreases from three to two to one, respectively, in this example. Moreover, the average number of stops per activity-travel chain increases from 2 to 3 to 6 in the example. In this example and all future references in this chapter, the count for the number of stops in an activity-travel chain includes the stop at the primary/terminating activity of the activity-travel chain. Hence, according to this definition, an activity-travel chain must have at least two stops

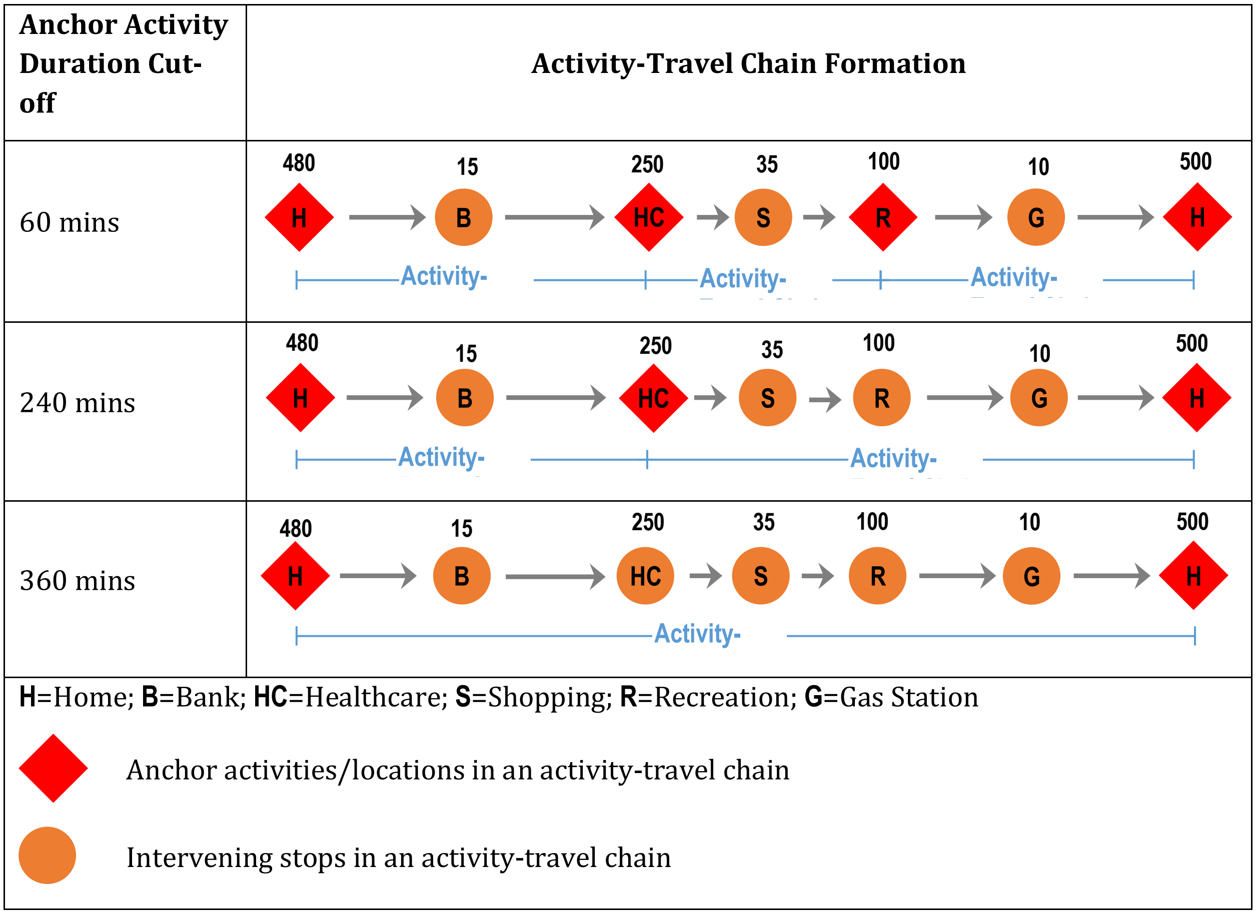
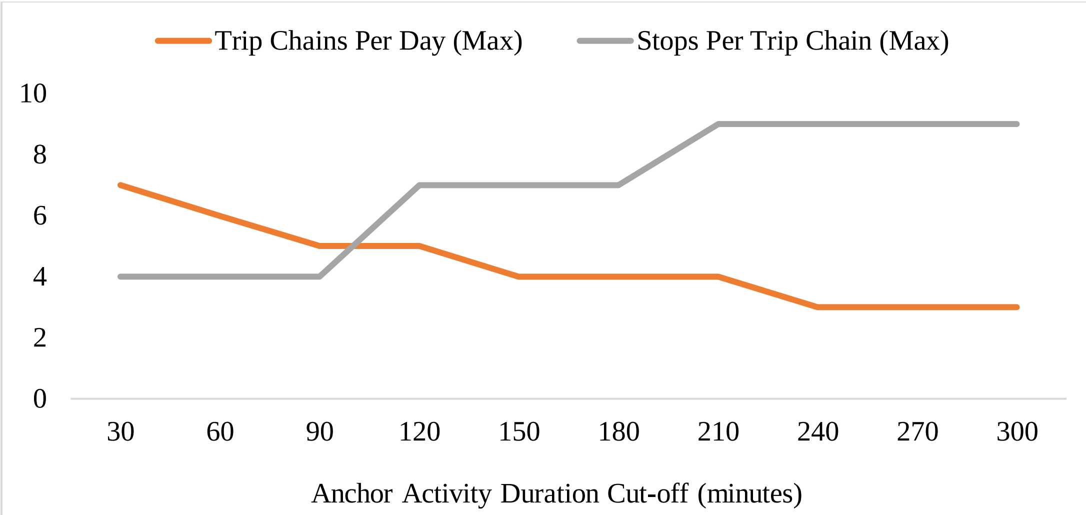


Figure 5: Formation of Activity-Travel Chains as a Function of Anchor Activity Duration Cut-off (values above circles represent activity durations)

Figure 6 displays the relationship between the anchor activity duration cut-off value and the maximum and average number of activity-travel chains per day and the stops per activity-travel chain. Unsurprisingly, as the anchor activity duration cut-off value increases the number of stops per activity-travel chain increases and the number of activity-travel chains per day decreases.

This study uses a four-hour cut-off value for anchor activity duration because lower cut-off values make it difficult to identify particularly important (or at least time-consuming) activities that an activity-travel chain maker conducts during a day and higher cut-off values basically produce the same set of activity-travel chains as the four-hour cut-off value. Moreover, the probability distribution of primary modes across activity-travel chain datasets (i.e., the mode splits for the primary mode of an activity-travel chain) changes very little when the anchor activity duration cut-off increases beyond four hours. As a result, defining activity-travel chains with an anchor activity duration of four hours or more seems to provide a good representation of activity-travel chains with important, or at least time-consuming, activities anchoring the activity-travel chains.

The operational definition of activity-travel chains resulted in 50,611 activity-travel chains made by 42,673 persons (from 31,169 households) after filtering out missing and invalid data. The percentage of all trips in the filtered dataset that are conducted within an activity-travel chain, as opposed to all trips, is 64%. Additionally, 52% of all persons in the filtered dataset make at least one activity-travel chain per day. For this 52%, they average 1.2 activity-travel chains per day per person. It should be noted that the anchor activity duration cut-off value also impacts the percentage of trips within activity-travel chains, and the percentage of trips within activity-travel chains increases with increases in the cut-off value.



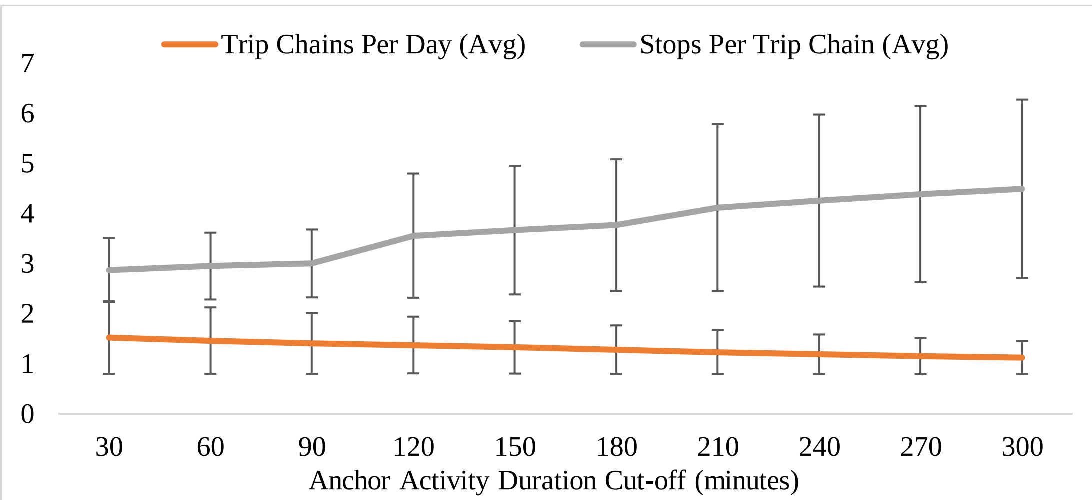


Figure 6: Max (Top) and Average (Bottom) Activity-Travel Chains per Day and Stops per Activity-Travel Chain as a function of Anchor Activity Duration Cut-off.
(Note: Error bars represent one standard deviation)

Since an activity-travel chain can only have one terminating anchor activity, defined as the last activity of an activity-travel chain or the primary activity, secondary activities are those for which stops are made within an activity-travel chain before the activity-travel chain's terminating stop. Therefore, an activity-travel chain should contain at least one secondary activity, otherwise it would be a direct trip.

5.3.2 Research Questions

The goal of this study is to explore the role ride-hailing currently plays within activity-travel chains. This goal is intentionally broad, given the exploratory nature of this research. To meet this goal and provide more specificity to guide the exploration/analysis, this subsection presents the study's two main research questions.

1. What characteristics of activity-travel chain makers, activities, and trips as well as the activity-travel chains themselves and the geographical areas in which the activity-travel chains occur, impact the propensity of activity-travel chain makers to use ride-hailing—as a primary or secondary mode—within an activity-travel chain?

2. What are the characteristics of activity-travel chain modes, makers, activities, and trips, as well as the activity-travel chains themselves and the geographical areas in which the activity-travel chains occur that impact the likelihood an activity-travel chain maker chooses ride-hailing as the primary activity-travel chain mode?

The first research question parallels the second objective of the study (mentioned in the Introduction) and effectively looks to compare activity-travel chains with one or more ride-hailing trips with activity-travel chains with zero ride-hailing trips. The second research question parallels the third objective of the study and focuses on the primary activity-travel chain mode and compares ride-hailing as a primary activity-travel chain mode to auto, transit, and walking as primary activity-travel chain modes.

5.3.3 Research Hypotheses

This subsection lays out the study's hypotheses related to the two research questions posed in the previous subsection. Although different modeling approaches are needed to answer the two research questions, the hypotheses laid out in this subsection do not differentiate between the propensity of activity-travel chain makers to use ride-hailing either as a primary or secondary mode (Research Question 1) and the likelihood an activity-travel chain maker chooses ride-hailing as the primary activity-travel chain mode (Research Question 2). However, this is not to say that the expectation is that the impact of each explanatory factor will be the same in the two models for the two choice situations. Conversely, because the choice situations are fundamentally different—Research Question 1 and the associated model focus on the choice of ride-hailing as either a primary or secondary mode within an activity-travel chain, while Research Question 2 and the associated model focus on the choice of ride-hailing as the primary mode only—the strong expectation is that the factors, particularly their relative magnitudes, will vary significantly across the two models. However, given the exploratory nature of the research study, and the dearth of existing theoretical and empirical research on ride-hailing in activity-travel chains, the authors do not have specific a priori expectations for the relative differences between most of the factors in each of the two models. One notable exception is for the stops per activity-travel chain variable, where the expectation is that ride-hailing usage will decrease with stops per activity-travel chain in both choice contexts but that the magnitude will be significantly higher for ride-hailing as the primary activity-travel chain mode choice context. The reason being that while ride-hailing may support complicated multi-modal activity-travel chaining, the authors do not expect travelers to make complicated, many stop, activity-travel chains exclusively or predominantly using ride-hailing given the costs of ride-hailing and the inability to store items between trips.

This subsection covers hypotheses related to modal attributes, activity-travel chain maker characteristics, activity types, activity-travel chain complexity and structure, and land-use characteristics. At a high level, this study hypothesizes that each of these categories of factors/variables will have a impact on the use of ride-hailing within activity-travel chains, and activity-travel chain mode choice in general.

Regarding modal attributes, given data limitations, this study does not focus on modal attributes. However, the statistical models do incorporate cumulative activity-travel chain travel time and cumulative activity-travel chain wait time, where the latter is only associated with transit trips. Naturally, the expectation is that as travel time and wait time increase, a mode becomes less attractive as a primary activity-travel chain mode. Even though modal attributes are critical to explaining variance in mode choice, this study focuses on the other attributes that also have important implications for forecasting travel behavior and planning transportation systems. Other than potentially land-use attributes and the activity-travel chain structure and complexity variables, the exclusion of other modal attributes from the statistical models is unlikely to bias the non-modal parameter estimates, as these factors are generally not systematically correlated with modal attributes.

Activity-travel chain maker attributes includes socio-demographic characteristics as well as transportation and travel related characteristics. Based on the empirical literature related to mode choice for individual trips, the expectation is that young, high-income, white males with a secondary degree and a full-time job are the most likely to use ride-hailing within activity-travel chains (Dias et al., 2017). Hence, the expectation is that older persons, persons from lower income households, non-white persons, females, persons with lower education attainment levels, and unemployed and part-time workers are less likely to use ride-hailing within activity-travel chains.

Regarding transportation characteristics related to activity-travel chain makers, the expectation is that persons who live in households with ample vehicles and persons who do not tend to use transit are less likely to use ride-hailing within activity-travel chains. The vehicle availability hypothesis stems from the idea that people who have ample access to a private auto would not benefit much from the attributes of ride-hailing, compared to walking and transit, in terms of activity-travel chaining because one's own auto is usually superior (except when parking costs are quite high). Moreover, empirical evidence suggests people with insufficient vehicles have a higher likelihood to use ride-hailing (Sikder, 2019). The transit usage hypothesis stems from empirical research in the literature finding that transit users tend to be likely users of ride-hailing (Feigon & Murphy, 2016a).

Regarding primary activity-travel chain activities, although the expectation is that primary activities do impact the use of ride-hailing with activity-travel chains, the magnitude and directionality for individual activity types is mostly uncertain. One notable exception is the eating out or meal activity, in which prior research suggests that areas within cities that have more restaurants tend to have higher usage of ride-hailing services (Ghaffar et al., 2020a).

Another set of attributes of interest relates to the structure and complexity of the activity-travel chain as a whole. The variables included in the statistical models related to activity-travel chain complexity include cumulative activity duration, cumulative travel distance or cumulative travel time, and total number of stops. The expectation is that all three attributes are likely to impact the likelihood of ride-hailing existing within an activity-travel chain.

However, there is no a priori definitive reasoning for the directionality of the impacts of these three parameters. Compared to private auto, ride-hailing activity-travel chains are probably likely to have fewer stops, given the ability to park a personal auto and store personal items between trips. However, compared to transit, ride-hailing activity-travel chains may have more stops, given the added convenience of door-to-door service provided by ride-hailing.

The activity-travel chain anchor activities variable included in the statistical models captures both the activity location/type at the beginning and the end of the activity-travel chain. Similar to the primary activity-travel chain activity, which only considers the activity location/type that terminates the activity-travel chain, the activity-travel chain anchor activities variable is likely to impact the use of ride-hailing within activity-travel chains, but the directionality of the relationship is mostly unclear a priori, except for the home-based socio-recreational anchor activity pairing.

Finally, another expectation is that land-use, specifically density, will impact the use of ride-hailing within activity-travel chains. Given previous research using travel survey data (Dias et al., 2017), as well as previous research using ride-hailing count data and models (Ghaffar et al., 2020b), there is a clear expectation that higher density regions are likely to have higher usage of ride-hailing within activity-travel chains.

5.4 Modeling Approach

To answer the research question proposed in Section 5.3.2 and to test the hypotheses laid out in Section 5.3.3, this study employs two different statistical modeling techniques. The first, focused on the first research question, is the binomial logit (BL) model. The second, focused on the second research question, is the nested logit (NL) model. These two models are laid out in the following two subsections. For a more detailed overview of the derivation of these models, please refer to Train (Train, 2009) and Ortúzar and Willumsen (Ortúzar & Willumsen, 2011a). In fact, much of the descriptions below are paraphrased from these two sources.

5.4.1 Binomial Logit

The first research question is interested in the propensity of an activity-travel chain maker to incorporate ride-hailing as a primary or secondary activity-travel chain mode, as a function of several categories of variables:

U: vector of attributes associated with the activity-travel chain maker.

C: vector of attributes associated with activity-travel chain structure, complexity, and activities

L: vector of land-use attributes associated with the city/region where the activity-travel chain occurs

Moreover, let X_i denote the set of all relevant attributes associated with activity-travel chain i; $X_i = \{U, C, L\}$.

To model the propensity of an activity-travel chain maker to use ride-hailing in an activity-travel chain with attributes X_i, this study employs the latent variable representation of the binomial logit (BL) model. Letting y_i^* represent the unobserved or latent propensity of the activity-travel chain maker to use ride-hailing in activity-travel chain i, the following mathematical relationships in Eq. 18-19 describe the latent variable representation of the BL model.

$$y_i^* = \beta X_i + \varepsilon_i \tag{18}$$

$$y_i = \begin{cases} 1 & y_i^* \geq 0 \\ 0 & y_i^* < 0 \end{cases} \tag{19}$$

In Eq. 19, y_i is a binary observable variable equal to one if activity-travel chain i includes ride-hailing and zero otherwise. In Eq. 18, β is a vector of parameters/coefficients associated with the variables in X_i. Moreover, ε_i represents the unobservable attributes impacting the activity-travel chain maker's propensity to include ride-hailing within activity-travel chain i. Under the assumption that ε_i follows the standard logistics distribution, the probability that activity-travel chain i includes ride-hailing (P_i) is shown in Eq. 20, where α is a constant parameter associated with ride-hailing's inclusion in the activity-travel chain.

$$P_i = \frac{exp(\alpha + \beta X_i')}{1 + exp\left(\alpha + \beta X_i'\right)} \tag{20}$$

To estimate the parameters α, β in Eq. 20, standard maximum likelihood estimation techniques can be used. These techniques are employed in STATA, the statistical modeling software used in this study.

5.4.2 Nested Logit

The second research question is interested in the propensity that an activity-travel chain maker chooses ride-hailing or another mode m as their primary activity-travel chain mode in activity-travel chain i. To address this research question, this study proposes a utility maximization framework (Eq. 21), i.e., an activity-travel chain maker will choose the mode m with the highest utility for activity-travel chain i.

$$m = argmax\left(U_{i,m}\right) \tag{21}$$

In Eq. 21, $U_{i,m}$ is the utility of mode m for activity-travel chain i. However, because utility is not fully observable, it needs to be separated into the observable component $V_{i,m}$ and unobserved component $\varepsilon_{i,m}$; $U_{i,m} = V_{i,m} + \varepsilon_{i,m}$. The observable component is the product of explanatory variables $X_{i,m}$, which are the same as in the previous subsection with the addition of attributes associated with mode m, and the vector of associated parameter values estimated, β_m, of which some depend on the mode m. Assuming the unobserved component $\varepsilon_{i,m}$ is independently and identically disturbed across modes and activity-travel chains and it follows the Gumbel distribution, then the probability that the activity-travel chain maker chooses mode m for activity-travel chain i is shown in Eq. 22.

$$P_{i,m} = \frac{exp\left(\alpha_m + X_{i,m}\beta_m\right)}{\sum_{k=1}^{|M|} exp\left(\alpha_k + X_{i,k}\beta_m\right)}, \qquad \forall m \in M \tag{22}$$

where,

- $P_{i,m}$: probability that individual i chooses mode m
- α_m: mode-specific constant for mode m
- $X_{i,m}$: vector of attributes associated with mode m for activity-travel chain i
- β_m: vector of coefficients for mode m
- M: the set of modes M, indexed by $m \in M$, which includes auto, non-motorized transport or NMT (walk, bicycle), ride-hailing, and transit (bus, rail).

Eq. 22 displays the multinomial logit (MNL) model with the independence of irrelevant alternatives (IIA) property that implies the error terms across all modes are assumed independent or uncorrelated. However, due to data limitations it is often the case that the error terms are correlated across modes, and different error term assumptions are necessary. This study employs the nested logit (NL) model that groups discrete alternatives into nests, in which the NL model captures correlation across modes within a particular nest, meaning that IIA holds within nests but not across nests. Section 5.6.2 provides details on the different nesting structures tested and the selected nesting structure for this study.

Let N denote the set of nests, indexed by $n \in N$. Also, let B_n denote the set of mode alternatives in nest n and let n_m denote the nest of mode m. The NL model assumes that the vector of unobserved utility components $\varepsilon_i = [\varepsilon_{i,1}, \dots, \varepsilon_{i,|M|}]$ has the following cumulative distribution in Eq. 23.

$$\exp\left(-\sum_{n\in N}\left(\sum_{j\in B_n}\left(e^{-\frac{\varepsilon_{i,j}}{\lambda_n}}\right)\right)^{\lambda_n}\right) \tag{23}$$

The marginal distribution of each $\varepsilon_{i,j}$ is univariate Gumbel but the $\varepsilon_{i,j}$'s are correlated within nests—they are not correlated across nests. Moreover, the parameter λ_n measures the degree of independence in unobserved utility among the alternatives in nest n. Or put alternatively, $1-\lambda_n$ is a measure of correlation for the alternatives in a nest n. Hence, if $\lambda_n = 1$, the alternatives in a nest are uncorrelated and the NL model reduces to the MNL model.

Given the cumulative distribution in Eq. 23, the probability that an activity-travel chain maker chooses mode m for activity-travel chain i is displayed in Eq. 24.

$$P_{i,m} = \frac{exp\left(\frac{V_{i,m}}{\lambda_{n_m}}\right)\left[\sum_{j\in B_{n_m}} exp\left(\frac{V_{i,j}}{\lambda_{n_m}}\right)\right]^{\lambda_{n_m}-1}}{\sum_{q=1}^{N}\left[\sum_{k\in B_q} exp\left(\frac{V_{i,k}}{\lambda_q}\right)\right]^{\lambda_q}}, \qquad \forall m \in M \tag{24}$$

where,

$P_{i,m}$: probability that the activity-travel chain maker chooses mode m for activity-travel chain i

$V_{i,m}$: deterministic component of the utility for mode m in activity-travel chain i, where: $V_{i,m} = \alpha_m + X_{i,m}\beta_m$. The terms have the same meaning as in the MNL model.

λ_{n_m}: logsum parameter of mode m's nest n_m denoting the degree of independence in unobserved utility among the alternatives in nest n_m

Similar to the BL model, the NL model and the MNL model can be estimated using standard maximum likelihood estimation techniques and such as those built into STATA, the statistical modeling software used in this study.

5.5 Data Overview

5.5.1 Data Source

This study relies on the household, person, and trip-level information from the 2017 NHTS, which is one of the few publicly available datasets that includes ride-hailing data. Based on the population density, this study analyses the 50 largest core-based statistical areas (CBSAs) from this dataset. Along with detailed information on daily trip, person, and household characteristics, the NHTS dataset also includes demographic information, such as the population and residential density.

Using the aforementioned data and definition of an activity-travel chain (discussed in Section 5.3.1 and Chapter 2), daily trips of each person were grouped into activity-travel chains. The resulting dataset, where an observation is an activity-travel chain, was then analyzed with the help of descriptive statistics to have a preliminary understanding of activity-travel chaining, associated mode choice, and the primary and secondary activities within each activity-travel chain.

The dataset contains a mode choice indicator for each trip. All persons in the dataset chose one or more of nine mode options to complete activity-travel chains. To have a more manageable statistical model, the observations were further restricted to represent a choice set of four primary transportation modes, namely, auto (all private vehicles including SUV and pickup trucks), non-motorized transport or NMT (walk, bicycle), ride-hailing, and transit (bus, rail). The excluded mode options (motorcycle, rental, and other modes) were not considered important in the context of this study due to their low share.

In the 2017 NHTS, the mode category for ride-hailing includes both taxis and trips ordered through transportation network companies (TNCs). Since this study defines ride-hailing as those trips provided by app-based TNC services, the study attempts to separate TNC trips from taxi trips, using a person-level variable that provides frequency of TNC app usage in the past month. This study categorizes trips made by persons who reported at least one TNC app usage in the past month as ride-hailing trips. Conversely, trips made by persons who reported zero TNC app usage are considered as taxi trips. Assuming accurate reporting by respondents, this categorization effectively removes trips from the ride-hailing category by travelers who definitely did not make a TNC trip. Conversely, a traveler who reports having used a TNC app in the past month may also have made taxi trips. However, the existing data does not allow us to fully distinguish between taxi and TNC trips. Nevertheless, the proposed classification should allow modelers and analysts to obtain a reasonable understanding of ride-hailing's role within activity-travel chains. The final model does not include taxi as a fifth primary mode because taxi is the primary activity-travel chain mode in only 0.1% of activity-travel chains, which resulted in non-convergent models.

5.5.2 Filtering

Before finalizing the activity-travel chain dataset for analysis, the dataset was filtered. First, the dataset was filtered to ensure the trips and activity-travel chains in the data were not based on highly irregular travel and activity patterns for an individual. Hence, entire person-days of travel were removed from the dataset if (i) they did not start their first trip of the day from home, or (ii) they did not return home at the completion of their last trip of the day.

Second, trips were filtered based on trip purpose in the NHTS dataset. Unfortunately, the publicly available 2017 NHTS dataset does not provide a separate activity dataset, so this study treats the trip purpose field provided in the trip dataset as the main activity at the end of each trip. For filtering, trips that were made for the purpose of exercise (e.g., jogging) were removed as they do not have an activity at the end of the trip. Additionally, trips that were made for the purpose of mode changes (e.g., walk trip to transit station) were combined with the next trip leg to form a multi-modal trip leg in an activity-activity-travel chain.

Third, distances and speeds were checked for each mode used in trips and all seemingly invalid observations were removed. Specifically, persons reporting distances greater than 3, 10, 80, 80, 40 and 40 miles when traveling with walk, bike, auto, transit, ride-hailing, and taxi, respectively, were removed from the dataset. In addition, those persons were removed from the dataset whose trips resulted in a calculated average speed greater than 5, 15, 70, 70, 70 and 70 miles per hour for walk, bike, auto, transit, ride-hailing, and taxi, respectively. Similarly, persons with travel speeds lower than 0.5, 2, 3, 3, 3 and 3 miles per hour for the aforementioned modes were also removed.

Fourth, activity-travel chains starting and ending at the home location with one intervening stop were removed from the dataset. This sequence of activities and trips is a simple round-trip and does not reflect a true activity-travel chain.

Lastly, outliers at the activity-travel chain level (e.g., total travel time, total travel distance, and total number of stops) were also removed. Specifically, all activity-travel chains with total travel time less than 5 minutes or greater than 720 minutes were filtered from the dataset. In the case of total travel distance, the lower bound was set at 0.1 miles while the upper bound was unrestricted as unreasonably long travel distances were captured through the other trip and activity-travel chain filters. The maximum value of the total number of stops in an activity-travel chain was based on the following formula: 1.5 times the interquartile range above the third quartile of the distribution. According to this calculation, the maximum allowable value for the number of stops is 9.5.

After filtering, the dataset contains observations pertaining to 42,673 persons from 31,169 households. The original dataset contained 97,453 persons and 50,982 households for the selected study area.

Before specifying the variables in the logit models, a collinearity check was conducted using variance inflation factor (VIF) and pairwise Pearson correlations. Considering all the regressors in the models, the maximum VIF was 3.47 with a minimum tolerance of 0.30, which is well within the acceptable ranges (Pearson, 2012). The correlation matrix of the model regressors also indicates that the magnitude of any of the pairwise correlations does not exceed 0.50 in most of the cases, while none of them exceed 0.80.

5.5.3 Descriptive Analysis

Table 9 displays a preliminary descriptive analysis of activity-travel chain patterns. The results indicate that the median (average) number of stops is four (four, respectively) for residents of the study area and the median (average) stop length is 112 (152) minutes. The median activity-travel chain distance and activity-travel chain travel duration are 22 miles and 70 minutes, respectively. Although the number of stops in a chain seems to vary widely, around 80% of the activity-travel chains are limited to five stops or less.

Table 9: Activity-Travel Chain Statistics

Statistics	Number of Stops	Total Activity Duration (mins)	Total Travel Distance (miles)	Total Travel Time (mins)
Min	2	1.0	0.11	5.0
Max	9	913	494	697
Average	4.3	152	30.2	83
Median	4	112	22.2	70
Standard Deviation	1.7	142	28.6	56

As anticipated, the proportion of activity-travel chain makers using ride-hailing as the primary mode is very low (0.28%) compared to other modes. The primary mode share for non-motorized transport (NMT), auto, transit, and ride-hailing are 3.9%, 93.3% 2.5%, and 0.3%, respectively. Clearly, as expected, the automobile is the most preferred mode among activity-travel chain makers.

Figure 7 displays the distribution of secondary modes in an activity-travel chain conditional on the primary mode of the activity-travel chain. The height of the bar indicates the proportion of all the activity-travel chains with a specific primary mode containing at least one trip with the secondary mode. Notably the secondary mode shares do not have to sum to 100%. In the case of NMT primary mode, 61% of these activity-travel chains also include auto, 6% transit, and less than 1% for ride-hailing and taxi. This indicates that many NMT activity-travel chains do not include a secondary mode. Conversely, in the case of ride-hailing primary mode, 57% and 72% of these activity-travel chains also include NMT and auto, respectively, and 17% include transit. This indicates that a large percentage of ride-hailing activity-travel chains do have at least one secondary mode if not two.

The results in Figure 7 indicate that NMT and auto are quite popular secondary modes. The share of NMT as a secondary mode is particularly high for transit and ride-hailing. The share of auto as a secondary mode is particularly high for transit and ride-hailing but is also dominant in NMT activity-travel chains. Interestingly, auto is more frequently the second mode of transit activity-travel chains than NMT. An investigation into the activity-travel chain dataset reveals that auto trip segments are common both before and after the transit leg in an activity-travel chain. Regarding the presence of auto trip after transit, the dataset provides evidence of mode switching occurring at home, which is possible due to the specific definition of activity-travel chain used in this study. It is also possible that the person using transit is picked up from the transit station by another person who is using auto.

The percentage of ride-hailing activity-travel chains where NMT is present is quite high and comparable with transit activity-travel chains. In contrast, the proportion of NMT is lowest (compared to its proportion in other primary modes) when auto is the primary mode. This behavior is likely because trip makers have less incentive to use other modes when they are already using auto within an activity-travel chain.

Activity-travel chains with ride-hailing as the primary mode are multi-modal in many cases (over 96%) and include NMT, automobile, and transit as secondary modes. On the other hand, ride-hailing is rarely used as a secondary activity-travel chain mode, which is not surprising given its low overall share. Although the share is very low (3%), the highest presence of ride-hailing as a secondary mode is found in transit activity-travel chains where the presence of taxi is also evident (1%).

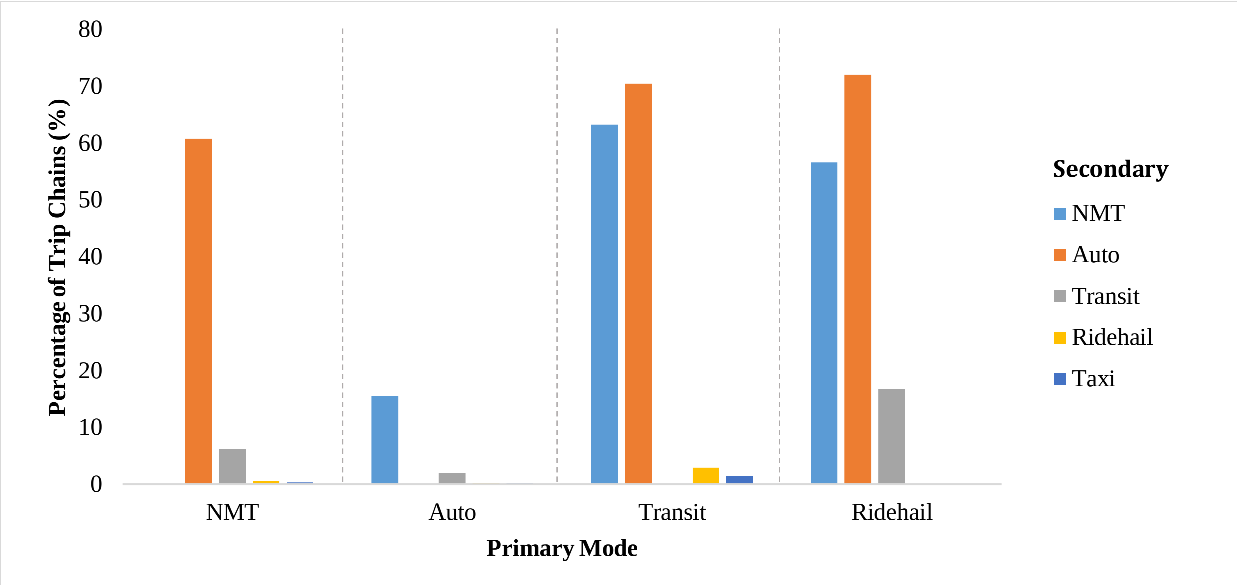


Figure 7: Distribution of Secondary Modes with respect to Primary Modes

Figure 8 illustrates the distribution of primary activity-travel chain activities across the four primary mode categories. Overall, work and shopping have a considerable share in all primary travel modes, and they also have the highest shares among all primary activities (33.3% and 21.7% activity-travel chains respectively). Home is highly dominant in NMT trips followed by work and shopping. The distribution of primary activity-travel chain activities is similar between auto and transit, except the latter has a slightly higher share of work trips.

While travelers mostly choose ride-hailing in activity-travel chains when they are traveling for work and shopping activities (53.8%), compared to other modes, ride-hailing has the highest share of activity-travel chains pertaining to healthcare, shopping, social/recreational, and meals. Ride-hailing is used less frequently for home and drop-off/pick-up trips than the other primary modes. This is an interesting finding and suggests that people are using ride-hailing services for significantly (in a practical sense) different primary activity-travel chain activities than existing travel modes. The role of ride-hailing in terms of transporting people to healthcare-based activities is likely something that researchers, transportation analysts, and policymakers should continue to monitor and consider in planning and policy making. The choice model results in Section 5.6 provide more detailed insights into this relationship, after controlling for other potentially spurious factors.

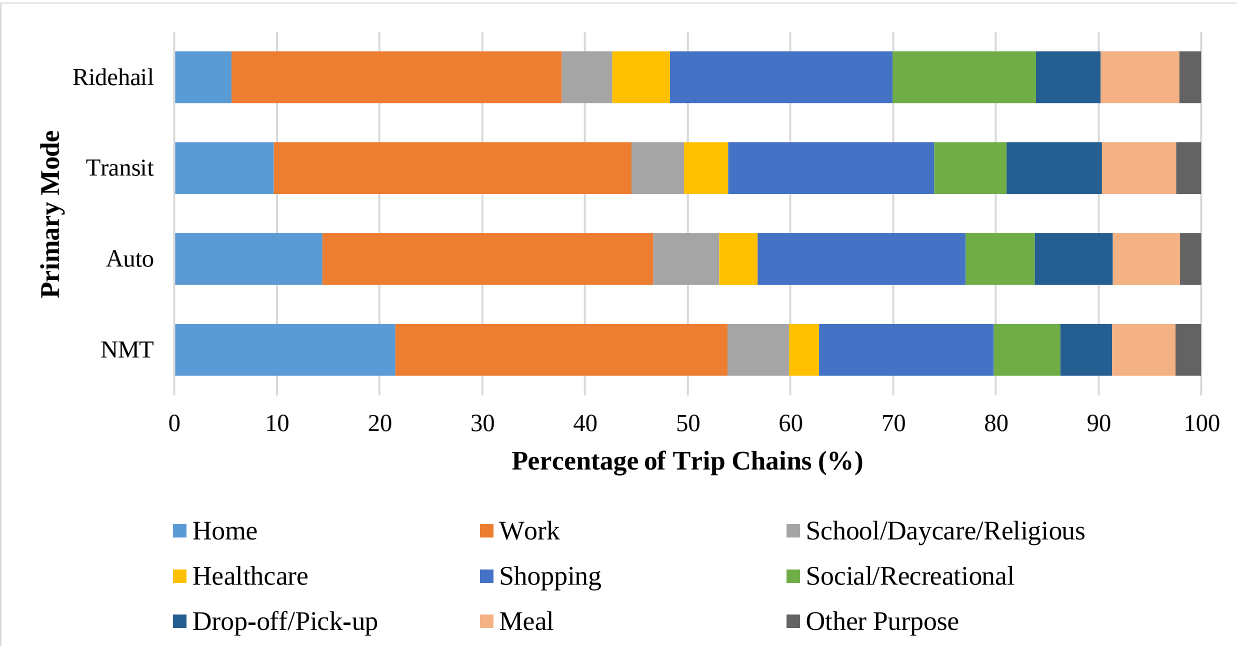


Figure 8: Distribution of Primary Activities in Activity-Travel Chains across Primary Modes

Figure 9 shows the distribution of secondary activities in activity-travel chains across primary modes. Home, shopping, and eating-out are dominant across all modes. Social/recreational and eating-out appear to have the highest share of activity-travel chains where the primary mode is ride-hailing; shopping and drop-off/pickup have the highest share where the primary mode is auto; whereas work and healthcare related stops have the highest share when the primary mode is transit.

Table 10 depicts the distribution of selected variables for the mode choice model across the four primary activity-travel chain mode alternatives. The table includes socio-demographic characteristics of activity-travel chain makers, travel characteristics of activity-travel chain makers, activity-travel chain structure and complexity, activity characteristics, and land-use characteristics. Only average transit wait time is excluded as it is only relevant to the transit mode. Except gender, the cross-mode distributions of all the variables are found to be significantly different considering the *p*-value of the chi-square test or ANOVA test.

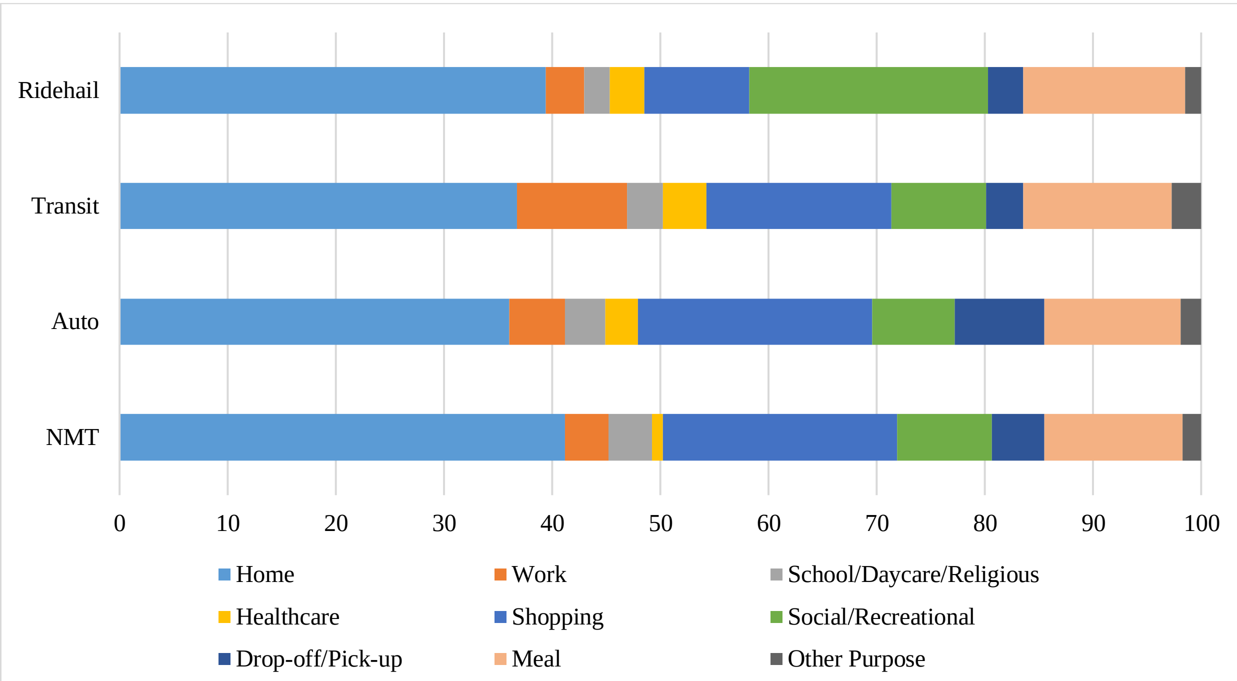


Figure 9: Distribution of Secondary Activities in Activity-Travel Chains across Primary Modes

Looking at the socio-demographic variables, there is almost no variation in gender across the use of primary modes. As expected, automobile and ride-hailing activity-travel chains are associated with medium to high income groups. Although ride-hailing is typically cheaper than a conventional taxi, the cost is still high and comparable to private car, which might explain its use by higher income trip makers. Buehler and Hamre (2015) find that high income groups have a greater tendency to make multi-modal trips than other income groups. Another significant difference across modes is found in the distribution of life cycle status.

The majority (87.4%) of activity-travel chain makers using ride-hailing do not have children in their household and a large proportion of them are employed. As travelling with children sometimes requires setting up car seats, it is unlikely that parents would opt for ride-hailing or transit when making multiple trips, especially if they own a vehicle. Finally, the distribution of age and education across modes, particularly ride-hailing, are consistent with much of the existing literature.

The variation across the modes in terms of travel day of the week is also quite high. The data shows that 33% of ride-hailing activity-travel chains are made on the weekend compared to 12% of transit, 22% of auto, and 26% of NMT.

Considering the variables pertaining to travel characteristics, there is considerable variation in public transit usage and vehicles per driver across the four modes. Apart from transit activity-travel chain makers, ride-hailing users have the second highest rate of public transit usage. Also, most of the activity-travel chain makers across NMT, automobile, and ride-hailing have at least one vehicle per driver in their household. This suggests that activity-travel chains with NMT and ride-hailing as primary modes are possibly substituting non-auto modes for auto trips. However, it is important to note that vehicle availability is the highest for auto (90.2%) activity-travel chains followed by NMT (60.1%), then ride-hailing (55.2%) and transit (44.7%).

Table 10: Descriptive Statistics for Four Activity-Travel Chain Modes

Variables	NMT (N=1,992)	Auto (N=47,229)	Ride-hailing (N=143)	Transit (N=1,252)
Socio-demographics of Activity-Travel Chain Maker				
Gender				
Male	48.04	45.78	46.85	47.76
Female	51.96	54.22	53.15	52.24
Age (years)				
16-35	31.43	20.51	55.94	34.19
36-65	48.29	54.39	32.87	51.52
66+	20.28	25.10	11.19	14.30
Household Income (USD)				
Low (≤25,000)	23.64	9.21	14.69	24.04
Lower Middle (25,000 to <50,000)	15.96	15.95	6.99	14.06
Middle (50,000 to <100,000)	24.05	31.59	27.27	23.72
Upper Middle (100,000 to <200,000)	24.10	32.19	27.97	25.32
High (≥200,000)	12.25	11.05	23.08	12.86
Ethnicity/Race				
White	67.04	74.11	72.03	56.38
Black	8.05	6.39	4.09	16.76
Asian	10.62	6.67	11.89	10.02
Hispanic	10.42	9.85	6.99	12.75
Other Race	3.88	2.99	4.20	4.09
Education				
Below Bachelor's Degree	42.48	43.90	20.98	36.21
Bachelor's Degree and Above	57.52	56.10	79.02	63.79
Life Cycle Status				
Working Adult without Children	42.97	34.48	72.73	58.15
Working Adult with Children 0-15	24.60	26.37	8.39	17.17
Working Adult with Children 16-21	5.12	7.32	4.20	6.47
Retired Adult without Children	27.31	31.84	14.69	18.21
Employment Status				
Unemployed	50.80	40.86	30.50	32.11
Part-time	12.52	11.97	8.51	11.57
Full-time	36.68	47.17	60.99	56.32
Travel Characteristics of Activity-Travel Chain Maker				
Public Transit Usage (days per month)	4.30	0.61	8.04	17.87
Vehicle Availability				
Low (< 1 vehicle per driver)	39.91	9.80	44.76	55.27
High (1+ vehicle per driver)	60.09	90.20	55.24	44.73
Day of Week				
Travel Day				
Weekend	26.41	22.09	32.87	11.90
Weekday	73.59	77.91	67.13	88.10
Activity-Travel Chain Complexity and Structure				
Cumulative Activity Duration (mins)	111.11	153.15	202.71	179.65
Cumulative Travel Time (mins)	59.71	82.26	85.08	141.56
Stops per Activity-Travel Chain	3.53	4.29	4.00	4.17
Activity-Travel Chain Activities				
Activity-Travel Chain Anchor Activities				
HBW	8.89	21.98	29.37	38.50
HBSHOP	3.97	3.08	2.10	1.04
HBSOCREC	1.61	1.89	14.69	1.60
HBO	12.10	11.07	9.79	9.66
NHB	73.44	61.97	44.06	49.20
Primary Activity-Travel Chain Activity (Main Purpose)				
Home	21.44	14.44	5.59	9.66

Variables	NMT (N=1,992)	Auto (N=47,229)	Ride-hailing (N=143)	Transit (N=1,252)
Work	32.38	32.19	32.17	34.90
School/Daycare/Religious	5.97	6.42	4.90	5.11
Healthcare	2.96	3.74	5.59	4.31
Shopping	17.02	20.26	21.68	20.05
Social/Recreational	6.53	6.74	13.99	7.03
Drop-off/Pickup	5.02	7.59	6.29	9.27
Meal	6.17	6.59	7.69	7.27
Other	2.51	2.04	2.10	2.40
Land-use				
Residential Density (HU per sq. mile)				
Low (0-499)	7.73	24.87	2.10	5.43
Medium (500-1,999)	23.24	42.89	14.69	19.57
High (2,000-9,999)	46.39	30.43	38.46	42.65
Very High (10,000-999,999)	22.64	1.81	44.76	32.35
Average Household Vehicle Ownership in CBSA	1.76	1.84	1.75	1.65

Note 1: Means are only used for continuous variables. For categorical variables percentage distribution is used.
Note 2: For each variable, except gender, there is a statistically significant difference across the four modes

There is also considerable variation across the four modes in terms of activity duration, travel time duration, and stops per activity-travel chain. Cumulative activity duration and cumulative travel time denote the total time within an activity-travel chain conducting activities and traveling between activities, respectively. In the NL model, the cumulative travel time varies by primary mode in the choice model. Given activity-travel chain i, the cumulative travel time for mode m is calculated as shown in Eq. 25,

$$CTT_{i,m} = \sum_{\boldsymbol{t \in Trips_i}} \boldsymbol{1_{m_t=m}} \times \boldsymbol{tt_t} + \sum_{t \in Trips_i} 1_{m_t \neq m} \times \frac{d_t}{u_m} \quad (25)$$

where,

$CTT_{i,m}$:	cumulative travel time for mode m in activity-travel chain i
$Trips_i$:	set of trips in activity-travel chain i, indexed by trip $t \in Trips_i$
1_A:	indicator function that returns a value of 1 if A is true, and zero otherwise
m_t:	travel mode of trip t
tt_t:	travel time of trip t
d_t:	distance of trip t
u_m:	average speed of mode m, where $u_{auto}, u_{NMT}, u_{transit}, u_{RH}$ are 22.3, 4.2, 11.9, and 13.8 mph, respectively

For example, if a traveler originally made three trips with distances 2 miles, 10 miles, and 15 miles via NMT, auto, and ride-hail, respectively, then Table 11 below shows the actual travel times for each leg of the trip as well as how the cumulative travel time is computed for each activity-travel chain mode $m \in M$ as in Eq. 25. For the ride-hailing mode option in the last row, Trip 3 was originally made with ride-hailing so the first term on the right-side of Eq. 25 is active and 55 minutes is the value used in this cell. Conversely, because Trip 1 and Trip 2 were not made with ride-hail, the second term on the right-side of Eq. 25 is active and used to compute/estimate the travel time in the counterfactual scenario where ride-hailing was used to conduct these two trips.

Table 11: Example Calculation of Cumulative Activity-Travel Chain Travel Time by Mode, based on Eq. 25

Trip → Mode ↓	Trip 1 Distance: 2 miles Actual Mode: **NMT**	Trip 2 Distance: 10 miles Actual Mode: **auto**	Trip 3 Distance: 15 miles Actual Mode: **ride-hail**	Cumulative Activity-Travel Chain Time
Actual	33 min	22 min	55 min	110 min
Auto	2mi / 22.3mph = 5.4 min	**22 min**	40.4 min	67.7 min
NMT	**33 min**	142.9 min	214.3 min	390.1 min
Transit	2mi / 11.9mph = 10.1 min	50.4 min	75.6 min	136.1 min
Ride-hail	2mi / 13.8mph = 8.7 min	43.5 min	**55 min**	107.2 min

The BL models includes cumulative travel distance, which is the same independent of mode so is not displayed in Table 10 in place of cumulative travel time. The BL model does not include cumulative travel time because cumulative distance effectively captures the choice context in which the activity-travel chain maker finds themself, when considering whether to use ride-hailing for one or more of the activity-travel chain segments.

Ride-hailing activity-travel chains have the highest activity durations followed by transit, auto, and NMT, with ride-hailing activity-travel chain activity durations being more than 50 minutes longer than auto. Regarding, activity-travel chain travel time, transit activity-travel chains easily have the longest travel time durations at 142 minutes, followed by ride-hailing and auto between 80 and 85 minutes, and then NMT at 59 minutes.

The activity-travel chain anchor activities variable captures the activities at the beginning and end of an activity-travel chain. The study includes five different anchor activity combinations, namely home-based work (HBW), home-based shopping (HBSHOP), home-based social/recreation (HBSOCREC), home-based other (HBO), and non-home based (NHB). Trips where one start or end activity type/location is shopping, and the other activity type/location is home are labeled HBSHOP. The HBO option captures the case where one start or end activity type/location is home and the other activity type/location is not working, social/recreation, or shopping. Finally, NHB denotes the case where neither the start the nor the end activity type/location is home.

Home, work, and shopping are the predominant primary activity-travel chain activities when people use automobile or NMT. For ride-hailing and transit activity-travel chains, work and shopping are the most common primary activities. Additionally, the share of HBSOCREC trips, in the activity-travel chain anchor activities category, is particularly high in ride-hailing activity-travel chains compared to the other three modes.

Ride-hailing also has a noticeably high share—comparable to transit—in areas with higher residential density. High density or core areas of a city are usually served by a variety of transit systems as they can run efficiently in these high demand areas. Ride-hailing services also tend to operate efficiently in higher density areas as vehicles do not need to travel a long distance (or wait a long time) between dropping of a traveler and picking up the next traveler.

This may indicate a potential substitution of ride-hailing for transit as ride-hailing services may provide a faster and more convenient travel option in some cases.

Table 10 also shows a statistically significant variation in the average household vehicle ownership in CBSA across the four modes. NMT and ride-hailing activity-travel chain makers reside in areas with similar average household vehicle ownership. As expected, auto and transit activity-travel chain makers live in areas with the highest and lowest average household vehicle ownership, respectively.

The descriptive statistics in Table 10 across the four modes provide a basis to estimate an activity-travel chain choice model. The statistics indicate significant differences across the four modes in terms of who is choosing each mode, the structure and complexity of the activity-travel chains, the primary activities associated with each mode, and even the residential density wherein the trips take place.

5.6 Choice Model Results

This section presents and discusses the activity-travel chain choice model estimation results. Section 5.6.1 presents the final specification and parameter estimates for the BL model wherein the dependent variable denotes the existence of ride-hailing in an activity-travel chain. Section 5.6.2 presents the MNL and NL model specifications and parameter estimates. The dependent variable in both the MNL and NL models is the primary mode of the activity-travel chain.

5.6.1 Specification and Estimation of the Binary Logit Model

Table 12 displays the final specification, the parameter estimates, and the statistical significance of the parameter estimates and the odds ratio for the BL model. The magnitudes of the coefficients indicate the change in log odds of including ride-hailing in activity-travel chain i due to a unit change in the independent variable of interest. Positive parameter values indicate an increase in propensity to choose/use ride-hailing, in one or more trip segments, within an activity-travel chain.

The odds ratio represents the probability of ride-hailing existing in activity-travel chain i over the probability of ride-hailing not being in activity-travel chain i, when an independent variable changes by one unit. Therefore, an odds ratio equal to 1, less than 1, or greater than 1 refers to a 50% probability, less than 50% probability and greater than 50% probability, respectively, of ride-hailing being in activity-travel chain i, when there is one unit increase in the independent variable.

Most of the coefficient estimates in the statistical models in Table 12 are consistent with observations made in Section 5.5.3 from the descriptive statistics, even after controlling for potentially spurious correlations; however, several of the model parameters in Table 12 indicate statistically insignificant relationships.

Table 12 indicates that gender, ethnicity/race, and employment status do not have a statistically significant effect on the use of ride-hailing in activity-travel chains. Conversely, persons aged 16-35, persons in households with annual incomes over $200,000, persons with a bachelor's degree, workers without children, weekend travelers, persons who use public transit, persons in households with fewer than one vehicle per driver, persons who live in higher density residential areas and in areas with a higher number of vehicles per household have a positive and statistically significant relationship with ride-hailing usage in trip-chains. Nearly all these findings are consistent with the existing ride-hailing literature for non-trip-chaining, although the life cycle status (i.e., whether or not travelers have children) is not commonly incorporated in most existing models.

In terms of the magnitudes of the activity-travel chain maker factors on use of ride-hailing, the parameter coefficients and the odds ratios indicate large impacts on ride-hailing usage in activity-travel chains. The results indicate that the odds of someone over 65 years old including ride-hailing in their activity-travel chain are 74% lower than someone between the ages of 16 and 35. Similarly, the odds of a working adult with a young child including ride-hailing in their activity-travel chain are 68% lower than a working adult without children. Also, the odds of a person with more than one vehicle per household member in their house using ride-hailing in an activity-travel chain are 48% lower than a person with more than one vehicle per household member. Moreover, compared with being from a low-income household and not having a bachelor's degree, being from a high-income household and having a bachelor's degree increases one's odds of using ride-hailing in activity-travel chains by 89% and 48% respectively.

The day of travel, weekend vs. weekday, also clearly plays a big role. Compared to a weekend day activity-travel chain, the odds of a weekday activity-travel chain including ride-hailing are 41% lower. This is a substantial difference and suggests ride-hailing plays a significantly bigger factor in activity-travel chains occurring on weekends.

In addition to the attributes associated with activity-travel chain makers and the areas in which they make activity-travel chains, Table 12 includes attributes related to the complexity and structure of activity-travel chains. According to Table 12, the inclusion of ride-hailing within an activity-travel chain is also positively associated with total duration of activities in an activity-travel chain, negatively correlated with the frequency of stops, and negatively correlated with cumulative travel distance. This set of results (total activity duration, stop frequency, total travel distance) indicate that travelers do not typically use ride-hailing in activity-travel chains to complete many long-distance trips to activities; rather, travelers use ride-hailing in activity-travel chains to travel relatively short distances between one or two relatively long duration secondary and/or primary activities. The odds ratio implies that increasing the stops per activity-travel chain by one stop decreases the odds of using ride-hailing by 12%.

The activity-travel chain anchor activities parameters in Table 12 suggest that activity-travel chains forming between home and shopping, and two non-home activities are less likely to incorporate ride-hailing compared to activity-travel chains forming between home and work; however, the difference is not statistically significant for home and shopping. Only HBSOCREC activity-travel chains have a higher tendency to include ride-hailing than a HBW activity-travel chain. These results suggest that ride-hailing currently plays the largest role in activity-travel chains that include a social/recreational activity at one activity-travel chain end and home as the other activity-travel chain end, which is mostly unsurprising. The odds ratio for the activity-travel chain anchor activities parameters indicates that the starting and ending anchor activities do play a big role in the inclusion of ride-hailing within activity-travel chains.

Table 12 also shows a variety of results related to primary activity-travel chain activity. All the non-home activities have a positive and statistically significant coefficient related to the home primary activity. The magnitudes for social/recreational and healthcare primary activities are noticeably large, indicating that all else being equal ride-hailing is quite frequently used for these two types of activities. The healthcare finding is particularly important, as it illustrates the possible important role ride-hailing plays in transporting travelers to healthcare activities along with intermediary activities along the way.

The residential density findings clearly illustrate their enormous impact on the use of ride-hailing within activity-travel chains. The odds of activity-travel chains within medium, high, and very high density areas including ride-hailing are 66%, 348%, and 1486% higher than activity-travel chains in low density areas. Additionally, the average household vehicle ownership in the CBSA where the activity-travel chain occurred implies that CBSA's with higher vehicle ownership are significantly more likely to incorporate ride-hailing in activity-travel chains.

Section 5.7 discusses the broader implications of several of these findings in more detail. Since, most of the socio-demographic and user travel characteristic results are consistent with the non-trip-chain ride-hailing literature, much of the discussion focuses on the results related to the activity-travel chain structure, activity-travel chain complexity, and activities associated with activity-travel chains that include ride-hailing.

Table 12: Results of the BL Model

Variables	Coefficient	z-Statistic	Odds Ratio
Intercept (Ride-hailing used in Activity-Travel Chain)	-6.300***	-7.790	0.002
Gender (Base = Male)			
Female	0.019	0.15	1.020
Age (Base = 16-35)			
36-65	-1.059***	-7.60	0.347
66+	-1.355***	-4.68	0.258
Household Income (Base = Low)			
Lower Middle ($25,000 to <$50,000)	-1.253***	-3.850	0.286
Middle ($50,000 to <$100,000)	-0.263	-1.130	0.769
Upper Middle ($100,000 to <$200,000)	-0.176	-0.740	0.839
High ($200,000+)	0.637*	2.540	1.891
Ethnicity/Race (Base = White)			
Black	0.112	0.420	1.118
Asian	-0.071	-0.340	0.932
Hispanic	-0.109	-0.500	0.897
Other Race	-0.255	-0.680	0.775
Education (Base = Below Bachelor’s Degree)			
Above Bachelor’s Degree	0.389*	2.270	1.475
Life Cycle Status (Base = Working Adult without Child)			
Working Adult with Child 0-15	-1.135***	-5.410	0.321
Working Adult with Child 16-21	-0.662*	-2.160	0.516
Retired Adult without Children	-0.512*	-2.000	0.599
Employment Status (Base = Unemployed)			
Part-time	-0.394	-1.520	0.675
Full-time	-0.122	-0.600	0.885
Public Transit Usage	0.023***	4.000	1.024
Vehicle Availability (Base = < 1 vehicle per driver)			
High (1+ vehicle per driver)	-0.650***	-4.140	0.522
Travel Day (Base = Weekend)			
Weekday	-0.532***	-3.450	0.587
Cumulative Activity Duration (mins)	0.005***	8.660	1.005
Cumulative Travel Distance (miles)	-0.006*	-1.990	0.994
Stops per Activity-Travel Chain	-0.127*	-2.220	0.881
Activity-Travel Chain Anchor Activities (Base = HBW)			
HBSHOP	-0.705	-1.150	0.494
HBSOCREC	0.874**	2.980	2.396
HBO	-0.770**	-2.810	0.463
NHB	-0.898***	-5.190	0.407
Primary Activity-Travel Chain Activity (Base = Home)			
Work	1.016***	3.400	2.762
School/Daycare/Religious	0.976*	2.510	2.653
Healthcare	1.515 ***	3.780	4.549
Shopping	1.201 ***	3.880	3.322
Social/Recreational	1.628 ***	4.830	5.093
Drop-off/Pickup	1.252***	3.540	3.497
Meal	0.882*	2.370	2.416
Other	0.963.	1.860	2.620
Residential Density (Base = Low)			
Medium (500-1,999)	0.507	1.550	1.660
High (2,000-9,999)	1.499***	4.820	4.475
Very High (10,000-999,999)	2.764***	8.290	15.859
Average Household Vehicle Ownership in CBSA	0.627.	1.860	1.872
Log-Likelihood	-1292.738		
LR χ2 or Wald χ2	962.620		
AIC	2665.477		
BIC	3017.794		

Note 1: All coefficient estimates are in reference to “no ride-hailing in activity-travel chain”.

Note 2: Sig. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.10

5.6.2 Specification and Estimation of the NL and MNL Model

Figure 10 displays the four nesting structures considered and tested in this study. The logsum parameter (λ) for the degenerate nests (i.e., the nest with only one alternative) are constrained to unity. According to Ortúzar and Willumsen (Ortúzar & Willumsen, 2011b), under this assumption, the nesting structure holds true if the estimated values of the logsum parameter fall in the range $0 < \lambda < 1$. This was found only for Nesting Structure (c), where NMT and transit share a nest, and ride-hailing and personal auto have their own degenerate nests. In Nesting Structure (c), the logsum parameter was significantly different than 1, with a value of 0.907. Hence, the final NL model structure is Nesting Structure (c).

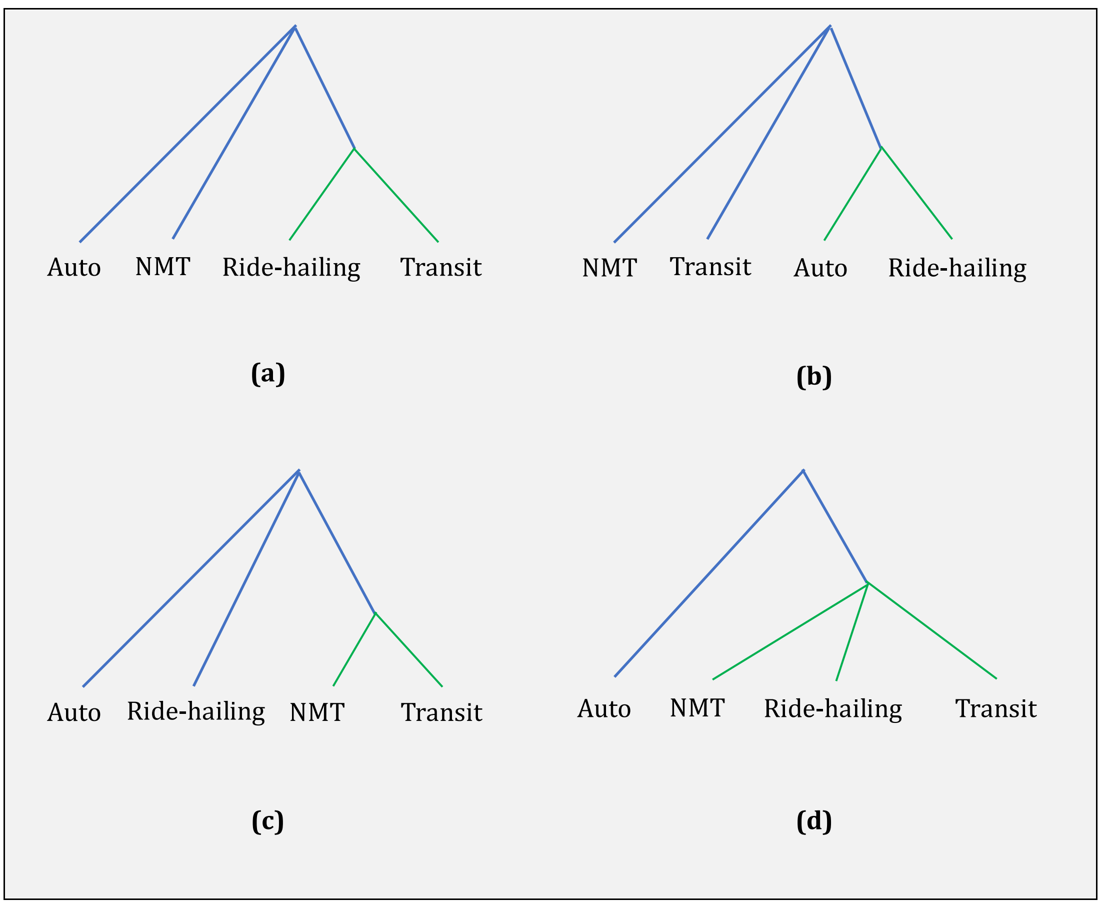


Figure 10: Alternative Nesting Structures for the Nested Logit Model

Table 13 displays the results of the NL model wherein the dependent variable is the primary mode of the activity-travel chain. The MNL model, with the same specification as the NL model, produced similar estimates and the results are provided in Table 14. Both tables display the coefficient estimates of the model parameters, their statistical significance, and the odds ratio. For each mode alternative, the coefficients represent the change in log odds of choosing a mode over auto when there is a unit change in a particular independent variable. Similarly, the magnitudes of the odds ratio for each alternative mode indicates the probability of choosing that mode over the probability of choosing auto when a factor changes by one unit. This study includes four primary modes, namely, auto, NMT, ride-hailing, and transit, wherein auto is treated as the base alternative. Like the BL model, the NL and MNL models were specified considering the variables in Table 10 with the addition of average wait time.

The NL model includes a statistically significant logsum parameter of 0.907 for the nest containing NMT and transit, suggesting a correlation between the error components of these two alternatives. In terms of model fit, the NL model is similar to the MNL model across all relevant metrics including log-likelihood, AIC, and BIC. Given the statistical significance of the NL logsum parameter, the following discussion will focus on the NL model results.

Alternative-specific Variables

Among the explanatory variables, only cumulative activity-travel chain travel time and average transit wait time were specified as alternative-specific variables. Please see Section 5.5.3 for a description of how cumulative travel time is calculated for each mode. The coefficients for the alternative-specific variables in both models indicate, consistent with basic transportation theory, that the propensity of choosing an activity-travel chain mode decreases with a rise in the cumulative activity-travel chain travel time and average transit wait time. Based on these two parameter values, the disutility for average wait time is higher than cumulative travel time but the ratio of the two is smaller than much of the existing literature (Frank et al., 2008; Frei et al., 2017; Idris et al., 2015; Wardman, 2004). The odds ratios imply that a one-minute increase in travel time in mode m and a one minute increase in transit wait time m, reduce the odds of an activity-travel chain maker choosing mode m by approximately 3% and 4%, respectively.

Choice of Ride-hailing versus Auto

According to Table 13, considering only the statistically significant parameters, ride-hailing services for activity-travel chaining are preferred by people who are younger (16-35 years), are from high-income households, are non-Hispanic, have high educational attainment, and are working adults without children. Additionally, in the case where unemployed is the base for employment status, both part-time and full-time coefficients are negative, statistically significant, and nearly equal in magnitude. This indicates that workers are less inclined to use ride-hailing in activity-travel chains irrespective of their work hour duration, compared to unemployed persons. The odds ratios for activity-travel chain makers older than 65, who are working with a child, and who work part time suggest compared to activity-travel chain makers between 16 and 35, who are working without children, and who do not work, indicate these factors significantly decrease the propensity to choose ride-hailing as the primary activity-travel chain mode compared to auto. The converse is true for high-income activity-travel chain makers and activity-travel chain makers with a bachelor's degree who are much more likely, to choose ride hailing as their primary activity-travel chain mode compared to the low-income activity-travel chain maker and activity-travel chain makers without a bachelor's degree.

Interestingly, the weekend parameter is statistically insignificant in the case of primary activity-travel chain mode for ride-hailing. This suggests that while Table 12 shows that the day of the week plays a big role for the existence of ride-hailing in activity-travel chains, Table 13 indicates it does not play a significant role in the choice of ride-hailing as the primary activity-travel chain mode. This requires further investigation, but one possibility is that users of ride-hailing within activity-travel chains are fundamentally different than activity-travel chain makers who use ride-hailing as their primary mode, and the former group may have a series of activities that are amenable to activity-travel chaining with ride-hailing on the weekend but not weekdays.

Ride-hailing activity-travel chain makers are also found to be more frequent transit users, which is similar to the BL model results. However, although vehicle availability (represented by vehicle per driver) has a negative parameter value, the parameter is insignificant in the NL model for ride-hailing. Also, unlike the BL model, the coefficient representing average household ownership in the home CBSA of the traveler is insignificant.

The cumulative activity duration and stops per activity-travel chain parameter values are similar in the NL and BL models for ride-hailing, with ride-hailing positively correlated with cumulative activity duration and negatively correlated with stops per activity-travel chain. This once again indicates that activity-travel chain makers tend to use ride-hailing to travel between a few activities with long durations. However, while the odds ratios are not directly comparable between the BL and NL model, the odds ratio, as hypothesized, is significantly lower in the NL model for the stops per activity-travel chain factor than the BL model.

The primary activity-travel chain activity results indicate that travelers are least likely to have home as the primary activity associated with an activity-travel chain. Among the non-home primary activities, healthcare and social/recreational activities are the most likely to be associated with a ride-hailing activity-travel chain. The significantly positive coefficient of HBSOCREC for activity-travel chain anchor activities category with the base being HBW also supports this finding.

The results also indicate a very strong relationship between the residential density of the activity-travel chain's location and ride-hailing as the primary activity-travel chain mode. As residential density increases, the model results indicate a statistically and steady (in terms of magnitude) increase in the propensity of activity-travel chain makers to choose ride-hailing. As residential density goes from low to high and low to very high, the odds of an activity-travel chain maker choosing ride-hailing over choosing auto increase by 439% and 3187%, respectively. These increases are substantially higher for ride-hailing than even transit and NMT, despite these latter two modes being associated with high usage in dense urban areas.

Similarities and Differences between NMT, Transit and Ride-hailing in Activity-Travel Chains

An in-depth discussion of the NMT and transit parameters is beyond the scope of this study. However, the differences between NMT and transit and ride-hailing parameters are worth noting. According to the model results, while gender is insignificant for ride-hailing and transit, it is a significant factor for NMT with a negative coefficient for female. Additionally, in terms of race, Black activity-travel chain makers have a positive coefficient for transit, negative for NMT, and negative but statistically insignificant for ride-hailing. Also, while the vehicle availability parameter is statistically significant and negative for transit, it is insignificant for NMT and ride-hailing. Transit has significant and positive coefficient for weekday activity-travel chains, which indicates a greater tendency of activity-travel chain makers to incorporate this mode in activity-travel chains formed on weekdays compared to weekends. This contrasts with the negative but statistically insignificant coefficient for weekday activity-travel chains for ride-hailing and the positive but statistically insignificant coefficient for NMT.

Regarding the activity-travel chain anchor activities variable, the coefficients suggest transit is primarily used for HBW tours, whereas ride-hailing is primarily used for HBSOCREC tours, and NMT for NHB tours. The parameters for the three non-auto modes are distinct in the activity-travel chain anchor activities category. If planners or policymakers are looking to plan a transportation system that reduces dependency on private auto, the differences in the activity-travel chain activity parameters for NMT, transit, and ride-hailing suggest that each different mode serves different, complementary, purposes and they may all be needed to allow travelers to forego auto ownership or near exclusive auto usage.

Table 13: Results of the NL Model

	Coefficients			z-Statistic			Odds Ratio		
	NMT	Ride-Hailing	Transit	NMT	Ride-Hailing	Transit	NMT	Ride-Hailing	Transit
Intercept	0.790*	-6.416***	-0.794.	2.350	-5.190	-1.720	2.203	0.002	0.452
Cumulative Travel Time (minutes)	-0.031***			-36.670			0.970		
Average Transit Wait Time (minutes)	-0.039***			-3.430			0.962		
Gender (Base = Male)									
Female	-0.199***	0.045	-0.161.	-3.370	0.240	-1.940	0.820	1.046	0.852
Age (Base = 16-35)									
36-65	-0.466***	-1.214***	-0.274**	-6.650	-5.770	-2.840	0.627	0.297	0.760
66+	-0.897***	-1.573***	-0.627***	-8.320	-3.970	-3.970	0.408	0.208	0.534
Household Income (Base = Low)									
Lower Middle ($25,000 to <$50,000)	-0.080	-0.858*	-0.420**	-0.760	-1.990	-2.760	0.923	0.424	0.657
Middle ($50,000 to <$100,000)	-0.217*	-0.080-0.050	-0.491***	-2.200	-0.240	-3.500	0.805	0.923	0.612
Upper Middle ($100,000 to <$200,000)	-0.115	0.691.	-0.246.	-1.130	-0.140	-1.690	0.891	0.951	0.782
High ($200,000+)	-0.006		-0.275	-0.050	1.880	-1.600	0.994	1.995	0.759
Ethnicity/Race (Base = White)									
Black	-0.252*	-0.661	0.723***	-2.000	-1.440	5.280	0.777	0.516	2.060
Asian	0.207*	-0.131	0.266.	2.080	-0.440	1.920	1.230	0.877	1.305
Hispanic	-0.157	-0.738*	0.054	-1.530	-2.020	0.390	0.855	0.478	1.055
Other Race	0.025	0.068	0.296	0.160	0.150	1.350	1.025	1.070	1.344
Education (Base = Below Bachelor's Degree)									
Above Bachelor's Degree	0.256***	0.645*	0.271**	3.780	2.460	2.670	1.291	1.906	1.311
Life Cycle Status (Base = Working Adult without Child)									
Working Adult with Child 0-15	-0.027	-1.153***	-0.457***	-0.350	-3.540	-4.020	0.973	0.316	0.633
Working Adult with Child 16-21	-0.379**	-1.027*	-0.187	-2.870	-2.050	-1.080	0.685	0.358	0.829
Retired Adult without Children	-0.239*	-0.535	-0.323*	-2.460	-1.490	-2.310	0.787	0.586	0.724
Employment Status (Base = Unemployed)									
Part-time	-0.193.	-0.868*	-0.755***	-2.000	-2.330	37.160	0.825	0.420	0.470
Full-time	-0.545***	-0.818**	-0.881***	-6.560	-2.860		0.580	0.441	0.414
Public Transit Usage	0.084***	0.105***	0.201***	15.550	9.480	37.160	1.088	1.111	1.223
Vehicle Availability (Base = < 1 vehicle per driver)									
High (1+ vehicle per driver)	-0.117	-0.340	-0.275**	-1.500	-1.550	-2.750	0.890	0.712	0.759
Travel Day (Base = Weekend)									
Weekday	0.085	-0.331	1.219***	1.180	-1.430	8.990	1.088	0.718	3.385
Cumulative Activity Duration	0.001***	0.006***	0.004***	3.860	6.510	10.130	1.001	1.006	1.004
Stops per Activity-Travel Chain	-0.302***	-0.455***	-0.270***	-9.530	-4.800	-6.820	0.739	0.634	0.763
Activity-Travel Chain Anchor Activities (Base = HBW)									
HBSHOP	-0.237	-0.267	-2.092***	-1.320	-0.410	-5.130	0.789	0.766	0.123
HBSOCREC	0.404.	1.567***	-0.548	1.700	4.190	-1.630	1.497	4.792	0.578
HBO	-0.450***	-0.806*	-1.367***	-3.460	-2.270	-8.260	0.637	0.447	0.255
NHB	0.359***	-1.080***	-1.093***	3.410	-4.030	-8.650	1.433	0.339	0.335
Primary Activity-Travel Chain Activity (Base = Home)									
Work	0.238**	1.462***	0.650***	2.750	3.500	4.370	1.269	4.313	1.915
School/Daycare/Religious	-0.295*	1.253*	0.232	-2.130	2.280	1.060	0.745	3.500	1.260
Healthcare	-0.089	1.943***	0.852***	-0.480	3.480	3.600	0.915	6.982	2.345
Shopping	-0.431***	1.299**	0.204	-4.290	2.950	1.250	0.650	3.666	1.226

	Coefficients			z-Statistic			Odds Ratio		
	NMT	Ride-Hailing	Transit	NMT	Ride-Hailing	Transit	NMT	Ride-Hailing	Transit
Social/Recreational	0.075	1.879***	0.686***	0.550	3.970	3.300	1.078	6.549	1.985
Drop-off/Pickup	-0.474***	1.388**	0.534**	-3.290	2.640	2.790	0.622	4.005	1.706
Meal	-0.177	1.362**	0.473*	-1.330	2.660	2.330	0.837	3.902	1.605
Other	0.094	1.457*	0.688*	0.480	2.000	2.390	1.099	4.294	1.989
Residential Density (Base = Low)									
Medium (500-1,999)	0.003	0.857	0.339.	0.030	1.370	1.930	1.003	2.355	1.404
High (2,000-9,999)	0.587***	1.684**	0.876***	5.790	2.790	5.190	1.799	5.387	2.402
Very High (10,000-999,999)	1.671***	3.493***	1.562***	12.680	5.660	8.080	5.320	32.868	4.767
Average Household Vehicle Ownership in CBSA	-0.341*	0.678	-1.415***	-2.380	1.400	-7.360	0.711	1.970	0.243
Log-Likelihood	-6949.174								
LR χ2 or Wald χ2	3941.550 (p = 0.000)								
AIC	14138.350								
BIC	15361.070								
Dissimilarity Parameter (λ)	0.907								
LR test for IIA (λ = 1): χ2	4.370 (p = 0.037)								

Note 1: N=46,115, 1,933, 141 and 1,222 for Auto, NMT, Ride-hailing and Transit, respectively

Note 2: All coefficient estimates are in reference to the choice of activity-travel chains with Auto.

Note 3: Sig. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.10

Table 14: Results of the MNL Model

Variables	Coefficients			z-Statistic			Odds Ratio		
	NMT	Ride-Hailing	Transit	NMT	Ride-Hailing	Transit	NMT	Ride-Hailing	Transit
Intercept	0.743*	-6.424***	-0.841.	2.180	-5.180	-1.760	2.102	0.002	0.431
Cumulative Travel Time (minutes)	-0.031***			-38.700			0.969		
Average Transit Wait Time (minutes)	-0.039***			-3.210			0.962		
Gender (Base = Male)									
Female	-0.199***	0.047	-0.167.	-3.340	0.260	-1.940	0.820	1.048	0.847
Age (Base = 16-35)									
36-65	-0.471***	-1.221***	-0.265**	-6.650	-5.800	-2.650	0.624	0.295	0.767
66+	-0.902***	-1.583***	-0.624***	-8.280	-3.990	-3.800	0.406	0.205	0.536
Household Income (Base = Low)									
Lower Middle ($25,000 to <$50,000)	-0.080	-0.857*	-0.426**	-0.750	-1.980	-2.690	0.923	0.424	0.653
Middle ($50,000 to <$100,000)	-0.217*	-0.072	-0.495***	-2.170	-0.220	-3.380	0.805	0.930	0.610
Upper Middle ($100,000 to <$200,000)	-0.117	-0.039	-0.239	-1.140	-0.110	-1.580	0.889	0.962	0.787
High ($200,000+)	-0.007	0.702.	-0.282	-0.060	1.910	-1.570	0.993	2.017	0.754
Ethnicity/Race (Base = White)									
Black	-0.269*	-0.660	0.778***	-2.100	-1.440	5.630	0.764	0.517	2.177
Asian	0.208*	-0.137	0.272.	2.070	-0.460	1.890	1.231	0.872	1.313
Hispanic	-0.159	-0.747*	0.066	-1.530	-2.030	0.460	0.853	0.474	1.069
Other Race	0.027	0.057	0.291	0.180	0.130	1.270	1.028	1.059	1.338
Education (Base = Below Bachelor's Degree)									
Above Bachelor's Degree	0.252***	0.652*	0.282**	3.700	2.480	2.680	1.287	1.919	1.325
Life Cycle Status (Base = Working Adult without Child)									
Working Adult with Child 0-15	-0.022	-1.156***	-0.484***	-0.280	-3.550	-4.120	0.978	0.315	0.616
Working Adult with Child 16-21	-0.388**	-1.035*	-0.171	-2.910	-2.060	-0.960	0.678	0.355	0.843
Retired Adult without Children	-0.240*	-0.533	-0.321*	-2.450	-1.480	-2.210	0.787	0.587	0.725
Employment Status (Base = Unemployed)									
Part-time	-0.190.	-0.874*	-0.770***	-1.960	-2.340	-4.740	0.827	0.417	0.463
Full-time	-0.542***	-0.823**	-0.899***	-6.460	-2.870	-6.500	0.581	0.439	0.407
Travel Day (Base = Weekend)									
Weekday	0.068	-0.325	1.303***	0.940	-1.400	9.520	1.070	0.722	3.681
Public Transit Usage	0.081***	0.106***	0.206***	15.070	9.440	41.800	1.085	1.112	1.229
Vehicle Availability (Base = < 1 vehicle per driver)									
High (1+ vehicle per driver)	-0.124	-0.335	-0.263**	-1.580	-1.520	-2.540	0.884	0.715	0.768
Cumulative Activity Duration	0.001***	0.006***	0.004***	3.730	6.520	10.270	1.001	1.006	1.004
Stops per Activity-Travel Chain	-0.303***	-0.454***	-0.262***	-9.430	-4.780	-6.410	0.738	0.635	0.770
Activity-Travel Chain Anchor Activities (Base = HBW)									
HBSHOP	-0.200	-0.273	-2.206***	-1.110	-0.420	-5.170	0.819	0.761	0.110
HBSOCREC	0.450.	1.562***	-0.620.	1.880	4.170	-1.770	1.568	4.767	0.538
HBO	-0.421***	-0.816*	-1.428***	-3.190	-2.300	-8.430	0.656	0.442	0.240
NHB	0.393***	-1.097***	-1.183***	3.680	-4.090	-9.580	1.482	0.334	0.306
Primary Activity in Activity-Travel Chain (Base = Home)									
Work	0.248**	1.468***	0.657***	2.840	3.510	4.240	1.281	4.340	1.930
School/Daycare/Religious	-0.294*	1.263*	0.244	-2.100	2.300	1.070	0.746	3.535	1.276
Healthcare	-0.077	1.951***	0.867***	-0.410	3.490	3.520	0.926	7.033	2.381
Shopping	-0.427***	1.300**	0.207	-4.210	2.950	1.220	0.652	3.669	1.230

Variables	Coefficients			z-Statistic			Odds Ratio		
	NMT	Ride-Hailing	Transit	NMT	Ride-Hailing	Transit	NMT	Ride-Hailing	Transit
Social/Recreational	0.078	1.884***	0.708***	0.570	3.970	3.290	1.081	6.583	2.031
Drop-off/Pickup	-0.491***	1.399**	0.574**	-3.350	2.660	2.900	0.612	4.053	1.775
Meal	-0.178	1.365**	0.494*	-1.320	2.660	2.340	0.837	3.916	1.639
Other	0.099	1.465*	0.695*	0.510	2.010	2.320	1.104	4.328	2.004
Residential Density (Base = Low)									
Medium (500-1,999)	0.0002	0.855	0.338.	0.000	1.370	1.870	1.000	2.351	1.402
High (2,000-9,999)	0.590***	1.681**	0.852***	5.770	2.780	4.900	1.805	5.370	2.345
Very High (10,000-999,999)	1.691***	3.492***	1.508***	12.710	5.660	7.620	5.425	32.847	4.519
Average Household Vehicle Ownership in CBSA	-0.311*	0.675	-1.504***	-2.150	1.390	-7.730	0.733	1.964	0.222
Log-Likelihood	-6951.360								
LR $\chi2$ or Wald $\chi2$	4957.260 (p = 0.000)								
AIC	14140.720								
BIC	15353.250								

Note 1: N=46,115, 1,933, 141 and 1,222 for Auto, NMT, Ride-hailing and Transit, respectively

Note 2: All coefficient estimates are in reference to the choice of activity-travel chains with Auto.

Note 3: Sig. codes: '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.10

5.7 Discussion

5.7.1 Consistency of Results with Study Hypotheses

The results from the BL, MNL and NL models support the high-level hypotheses laid out in Section 5.3.3 that modal attributes, activity-travel chain maker characteristics, activity types, activity-travel chain complexity and structure, and land-use characteristics impact the propensity of activity-travel chain makers to use ride-hailing with activity-travel chains. The following three subsection focus on three particularly important and interesting relationships between explanatory variables and ride-hailing usage.

Ride-hailing and Primary Activity-Travel Chain Activity

The choice of ride-hailing within activity-travel chains is strongly associated with healthcare as a primary activity which signifies the important role ride-hailing services currently play in providing access to healthcare facilities. Considering the negative association between ride-hailing use and vehicle availability in the BL model, it is also plausible that people with zero or low access to personal vehicles use ride-hailing services as a substitute (in at least one part of activity-travel chain) to access essential services, where healthcare is just one example.

The healthcare finding is arguably the most important in the study. It indicates that ride-hailing plays a critical role in the current transportation system. Policymakers interested in ensuring access to healthcare and other essential services across ages, incomes, races, and genders, may consider ensuring access to the ride-hailing services that can and currently do provide transport to healthcare facilities. This may take the form of subsidies for riders to make certain trips. Or it may take the form of working with health insurers and healthcare providers to promote ride-hailing as a means of transport to healthcare facilities.

The particularly interesting thing about this finding is that even when travelers chain multiple trips on the way to the primary healthcare activity, ride-hailing still plays an important role. This means that travelers are not just ride-hailing from home to a healthcare facility. They are conducting other secondary activities before arriving at a healthcare facility. This further indicates the potential value of ride-hailing as a mode that enables activity-travel chaining.

The choice of ride-hailing within activity-travel chains is also strongly associated with social/recreational primary activities. Although this is an unsurprising finding, it is nevertheless important to understand the role ride-hailing plays in the current transportation system. The model results in this study indicate that ride-hailing does play an important role connecting travelers to social/recreational activities, even in the context of activity-travel chaining.

Ride-hailing and Activity-Travel Chain Attributes

The model contains two main attributes to capture activity-travel chain structure and complexity, namely, activity duration and stops per activity-travel chain. More stops per activity-travel chain coincide with a more complex activity-travel chain, as they require more cognitive effort to sequence the activities, schedule the activities and trip start times, and determine modes and routes to travel between activity pairs. Although maybe less obvious, longer activity durations are also assumed to increase complexity because, all else being equal, longer activities by definition consume more hours in a day. A reduction in available hours per day to move between activity locations effectively constrains an activity-travel chain maker's ability to sequence and schedule travel between activities as well as execute travel itself.

The findings in Table 13 indicate that longer activity durations and fewer stops per activity-travel chain increase the likelihood of users choosing NMT, ride-hailing, and transit relative to the personal vehicle. However, the magnitude is highest for ride-hailing across both attributes. Looking at stops per activity-travel chain, the results indicate that the private auto dominates activity-travel chains with more stops (i.e., higher complexity or level of difficulty). Looking at activity duration, it appears that when activity durations increase, non-auto modes are more prevalent. Hence, it appears that auto is most valuable when an activity-travel chain maker needs to make numerous stops, where the cumulative stop time is relatively short.

In previous research, Ye et al. (2007) examine the impact of activity-travel chain complexity on mode choice in work and non-work tours. Following some of the suggestions (pertaining to transit) provided in Ye et al. (2007), an increase in ridership in ride-hailing and/or other shared mobility services (e.g., conventional ridesharing, ride-splitting, bikesharing, micro-transit, etc.) could be achieved by locating multiple and diverse activities at a single location in order to allow activity-travel chain makers to satisfy their needs/demand for multiple activity types while reducing the number of stops.

Ride-hailing and Activity-Travel Chain Maker Attributes

Results from BL and NL models also reveal some important findings relevant to activity-travel chain makers and their propensity to use ride-hailing. While some of the variables like age, household income, and auto ownership have their usual association with the use of ride-hailing (independent of activity-travel chains) reported in recent studies (Alemi et al., 2018; Feigon & Murphy, 2016b), there are additional factors that appear to be influenced by activity-travel chaining. For example, ride-hailing activity-travel chains are less popular among workers who have children aged 0-15 years. These parents would likely be highly inconvenienced by the lack of a car seat in ride-hailing (and/or transit) vehicles and would likely rely on their own personal auto to complete activity-travel chains. This also implies that special care may need to be taken for parents of young children within ride-hailing services if ride-hailing companies want to serve this market.

Another notable modeling result is that frequent transit users have a high likelihood of using ride-hailing (and transit) for activity-travel chains. This suggests that ride-hailing services are providing significant mobility benefits, in the context of activity-travel chains, to public transit users.

The model results also indicate that residential density has a very strong association with ride-hailing activity-travel chaining. As discussed by Conway, Salon and King (2018), the relationship is reasonable as ride-hailing trips are usually shorter and less costly in dense areas, where activities are closer and parking is very expensive and/or very difficult to find. A particularly striking finding is that the effect of density on ride-hailing is at least twice the size of density's effect on NMT and transit, despite NMT and transit usage being known to have a strong positive relationship with density (Chakrabarti & Shin, 2017; Saelens & Handy, 2008). With activity-travel chaining, the higher preference for ride-hailing services in high density areas could result from the low wait times and the need to make fewer stops (due to activity clustering) in dense areas. The conjecture regarding activity clustering in dense areas is supported by the relatively high walk trip percentage as a secondary mode associated with ride-hailing found in Figure 7.

5.7.2 Consistency of Results with Existing Literature

In addition to the novel findings discussed in the previous section, there are also some findings which are inconsistent with the existing activity-travel chain literature. Researchers analyzing activity-travel chaining behavior have observed that women are usually more involved in activity-travel chains than men, particularly in households with children (Kumar & Levinson, 1995; McGuckin & Murakami, 1999). However, this study did not find any significant difference between the activity-travel chain mode preference of women and men for ride-hailing. The results only shows that women have a lower tendency to choose NMT and transit than men. This outcome could be due to the current models' inability to distinguish mode preference across different trip purposes and gender. Moreover, the activity-travel chain mode choice may be significantly influenced by the number and age group of children on the trip, which the models do not incorporate due to data availability.

5.8 Conclusion

5.8.1 Summary

The personal auto offers many advantages over transit and NMT modes in activity-travel chaining. Vehicle-based mobility services such as ride-hailing offer many of the activity-travel chain advantages of a personal auto including scheduling and route flexibility compared to transit and short travel times compared NMT modes. However, with ride-hailing services, travelers face difficulty when traveling requires moving with additional items, like a child car seat or even groceries and other shopping items. Moreover, ride-hailing is a relatively expensive travel mode. Given the similarities and differences between ride-hailing and the personal auto in terms of completing activity-travel chains, this study aims to assess the attractiveness of ride-hailing as a trip-chain mode. To this end, this study estimates a BL model, an MNL model, and a NL model to explicate the choice of ride-hailing as a mode in any segment of the activity-travel chain and also as a primary activity-travel chain mode (based on distance).

The modeling results include the novel findings that ride-hailing activity-travel chains are more likely to terminate in healthcare and social/recreational activities than auto, NMT, and transit. The social/recreational findings are unsurprising given the clear benefit of not needing to drive to/from events where alcohol may be consumed and/or parking may be expensive. The healthcare finding is particularly interesting, as it indicates ride-hailing provides travelers who need healthcare a valuable travel option. Moreover, the significantly high coefficient for healthcare in the case of ride-hailing suggests a potential role for planners and policymakers or even healthcare providers in leveraging ride-hailing to further improve access to healthcare facilities. Making healthcare facilities accessible via ride-hailing may entail designating pickup and drop-off locations at healthcare facilities for ride-hailing vehicles or incentivizing ride-hailing companies to transport travelers to healthcare facilities that are located near the suburban-rural or suburban-exurban divide.

Several findings in this study are consistent with observations in previous ride-hailing studies that focus on individual trips rather than activity-travel chains (Alemi et al., 2018; Dias et al., 2017; Feigon & Murphy, 2016b). For example, this study and previous studies find positive relationships between ride-hailing and persons who: are younger, highly educated, live in high-income households, use public transit frequently, and reside in high-density areas. In addition, there are similar findings on increased tendency to use ride-hailing during weekends.

Another takeaway from this study is that persons who use ride-hailing for activity-travel chaining are also frequent transit riders. While a single cross-section of activity-travel chains does not permit strong claims about whether ride-hailing is a complement or substitute to transit, the empirical finding in this study clearly indicates a relationship between the two modes in the context of activity-travel chaining. In the case where ride-hailing does complement transit on an individual trip level, there is a need to plan and manage a multi-modal transportation system to integrate public transit and ride-hailing services. However, in the NHTS data, the percentage of ride-hailing trips that act as first- or last-mile feeder to transit within activity-travel chains is less than 10% of all ride-hailing trips, indicating that ride-hailing is not a substantial complement to transit in this way. Nevertheless, there are other mechanisms by which ride-hailing and transit may be complementary services within activity-travel chaining, namely, ride-hailing may allow travelers to forego vehicle ownership or purchasing an additional vehicle, thereby resulting in travelers substituting both ride-hailing and transit trips for previous personal auto trips. Similarly, ride-hailing may complement transit via enabling travelers to take transit to a major activity center during the peak period when the traveler also needs to travel to areas that are not well connected with transit during the off-peak period but can be served by ride-hailing.

The study also indicates that as activity-travel chain complexity increases, ride-hailing tends to be the least preferred primary activity-travel chain mode. Activity-travel chain makers are less likely to use ride-hailing with an increase in activity-travel chain stops (compared to personal automobile) than even transit and NMT. This finding suggests that the benefits of a personal auto for activity-travel chaining, relative to a ride-hailing service for activity-travel chaining, are quite significant and may limit the ability of households to forego auto ownership.

5.8.2 Limitations

To separate ride-hailing users from the NHTS combined category for ride-hailing/taxi, this study uses the data on TNC app usage and assumes that people who used the ride-hailing app at least once in the past 30 days are ride-hailing users. Although this is a strong assumption, this is the only information available which could reasonably differentiate ride-hailing users from taxi users. The authors anticipate and hope that future NHTS data will distinguish between ride-hailing and taxi trips. The dataset is also missing relevant modal attributes that would be useful for a mode choice analysis, such as travel cost, wait time, transit transfers, etc. The analysis would also benefit from a higher spatial resolution (e.g., census tracts or block groups), trip destination location information, and a distinction between delivery work trips (i.e., food delivery) and other work trips.

The study is also limited by several assumptions that support the analyses. For example, it is assumed that mode choice is dependent on activity-travel chain complexity, not the other way around. Although this assumption is supported by Ye et al. (2007) using Swiss Travel

Survey dataset, the order of preference between choice of mode and activity-travel chain complexity has not been investigated using the 2017 NHTS dataset.

This study also does not consider the trip making dependency between household members that can influence activity-travel chaining characteristics. In households, some trips or activities can be shared (e.g., recreation, eat-out, etc.), whereas others are carried out by one of the household members (e.g., grocery shopping, dropping-off or picking-up children from school). In case of the latter, it is highly likely that with the increase in one household member's activity-travel chaining complexity, there will be a decrease in the activity-travel chaining complexity of the other household member. An investigation of this interrelationship between the activity-travel chaining pattern of household members would require the incorporation of household activity distribution into the modeling framework, which I aim to exploring in future extension of this study.

In terms of the model structure, the study assumes a, one-directional, relationship between each of the explanatory variables and either the choice to include ride-hailing within an activity-travel chain or the choice of ride-hailing as the primary activity-travel chain mode. A more complex model structure, such as structural equation models, can test and capture for simultaneity and/or reverse causation. Examples of potential simultaneity or reverse causality include public transit usage, vehicle availability, cumulative activity duration, and stops per activity-travel chain. The usage of ride-hailing in general as well as within activity-travel chains may cause transit usage to increase directly or indirectly through decreases in car ownership. As such, it is also conceivable that ride-hailing propensity (within activity-travel chains) impacts car ownership. Finally, if mode choice and activity-travel chain structure decisions are made jointly, then simultaneity bias may impact the coefficient estimates for number of stops—a personal auto enables more stops than NMT, transit, or ride-hailing in most cases—and cumulative activity duration—as slower modes reduce the amount of time travelers have to conduct activities.

5.8.3 Future Research

Although this study provides valuable insights into the role of ride-hailing within activity-travel chains, the data limitations mentioned in the previous subsection limit the range of research questions related to ride-hailing and activity-travel chains that can be answered. Hence, an important future research direction involves collecting different types of data on the propensity of travelers to use ride-hailing within activity-travel chains. Both panel surveys that capture behavioral changes over time and stated preference surveys that allow hypothetical activity-travel chaining options could provide deeper insights into the role of ride-hailing within activity-travel chains.

Specifically, panel and stated preference surveys could provide insights into the modal substitution effects between ride-hailing and transit within activity-travel chains and between ride-hailing and personal auto within activity-travel chains. Understanding these substitution effects is critical to developing policies to make urban transportation systems more sustainable and efficient.

Finally, the relationship between ride-hailing activity-travel chains and residential density found in this study necessitates further exploration because the demand for many auto trips within a short period in a core area can worsen congestion, if ride-hailing replaces walking, biking, or transit and if ride-hailing services continue to have high deadheading miles between occupied travel. This issue is important because up to 40% of the ride-hailing trips are observed to operate in peak hours in several high-density urban areas like Los Angeles, San Francisco, Chicago, New York, and Boston (Feigon & Murphy, 2018; Gehrke et al., 2018). In general, with the availability of more detailed data on the location of activities and individual trips (e.g., number of items carried by the trip makers, scheduling or routing constraints, etc.) the authors would like to extend the research to include more built environment factors and compare the activity-travel chaining pattern of ride-hailing trips with unchained activity-travel pattern.

CHAPTER 6: DISSERTATION CONCLUSIONS

6.1 Summary

i. In my dissertation, I analyzed activity-travel chaining behavior from the perspectives of identifying its prevailing types, analyzing its effect on peak and off-peak motorized PMT and exploring its relationship with ride-hailing use. More specifically, my dissertation is motivated by the following three research questions. What are the prevailing types of activity-travel chains as characterized by the activity and travel characteristics within activity-travel chains?

ii. How does activity-travel chaining affect peak and off-peak travel demand?

iii. What attributes of riders and activity-travel chains are associated with the choice of ride-hailing in activity-travel chains?

I developed three studies to answer these questions with the help of the 2017 National Household Travel Survey dataset and the 2018-2019 Household Travel Survey data collected from four MPOs in the United States – Chicago Metropolitan Agency for Planning (CMAP), Puget Sound Regional Council (PSRC), Sacramento Area Council of Governments (SACOG), and Whatcom Council of Governments (WCOG). For data analysis, I employed multiple statistical tools, such as Latent Class Analysis (LCA), multi-level Poisson regression, structural equation modeling, and logistic regression.

The study in Chapter 3 is motivated by the first question. Using the activity-travel chain dataset derived from the 2018-2019 Household Travel Survey dataset of four MPOs, I classified the activity-travel chains using latent class analysis (LCA). I identified four distinct types of activity-travel chains where the most representative type involves simple car-based activity-travel chains with short-duration stops, typically for maintenance activities. Among the four types of activity-travel chains, one exclusively represents non-motorized transport

(NMT)- and transit-based activity-travel chains. I also analyzed the propensity of travelers to conduct each type of activity-travel chain using multi-level Poisson regression model. The results show that travelers in households with children and older travelers more frequently make car-based activity-travel chains for maintenance activities. Moreover, travelers in single-member households, and travelers who are younger and male more frequently make NMT- and transit-based activity-travel chains for maintenance activities.

The study in Chapter 4 pertains to the second question. Using the same activity-travel chain dataset from four MPOs, I investigate the structural relationship between activity-travel chaining propensity and motorized person-miles traveled (PMT) during the peak and off-peak periods of the day. I built two models, one with worker sample and the other with non-worker sample to compare the resulting relationships. My structural equation modeling framework for the two models also incorporates mediating factors such as travel time savings from activity-travel chaining, average daily trips, activity space and mode share when measuring the effect of activity-travel chain propensity on motorized PMT. The results show that chaining of subsistence, maintenance and discretionary activities increases peak motorized PMT of both workers and non-workers, providing the strongest evidence in the literature that activity-travel chaining can exacerbate traffic congestion during peak travel periods of the day. The results also indicate that decreases in peak-PMT are associated with increases in off-peak PMT when chaining maintenance activities, which suggest the substitution of these activities in the peak period with same or similar chained activities during the off-peak period.

The study in Chapter 5 answers the third and last question. In this study, I investigated the characteristics of the activity-travel chain makers who use ride-hailing in activity-travel chains and attributes of activity-travel chains, activities, modes and location associated with ride-hailing. For the analysis, I employed both binary and nested logit models using activity-travel chain dataset derived from the 2017 NHTS. The results show that young persons, frequent transit users, and those having long-duration stops prefer ride-hailing over car. Also, activity-travel chain makers headed to healthcare and social/recreational activities have a particularly high tendency to use ride-hail.

6.2 Major Contributions

My dissertation has three major contributions. Chapter 3 reveals the existence of four distinct activity-travel chain types. Unlike other activity-travel chain studies that include few indicators, specific mode category or aggregate level analysis, my study includes several activity-travel attributes that jointly define each activity-travel chain type and includes a three-level Poisson prediction model to associate the daily activity-travel chaining propensities of each activity-travel chain type with socio-demographic characteristics while controlling for both person and household effects. Chapter 4 investigates the links between activity-travel chaining propensity and motorized PMT. To the best of my knowledge, this is the first study that directly measures the impact of activity-travel chaining on travel demand (peak and off-peak motorized PMT) using complex path analysis through structural equation modeling and thus have important policy implications for travel demand management. Finally, Chapter 5 contains the first investigation into activity-travel chains incorporating ride-hailing as a primary mode or secondary mode using nested and binary logit models.

The findings from my three studies indicate the importance of activity-travel chaining in understanding travel behavior and manage travel demand. Thus, local and regional transportation and land use planning need to consider activity-travel chaining behavior when forecasting travel demand. My analysis also suggests that increased mix of compatible land uses and improved walking and biking network results in smaller activity spaces and more NMT mode share, all of which reduces peak PMT associated with activity-travel chaining. Moreover, emerging transportation modes, like ride-hailing can provides significant benefits to activity-travel chain makers, especially in a well-designed multi-modal transportation system. Referring to the strong positive correlation between transit and ride-hailing mode usage, there is a potential to shift some of the peak-hour activity-travel chains to off-peak hour by improving ride-hailing service to important activity centers, which have poor transit service during off-peak hours.

6.3 Limitations and Future Research

My dissertation has several limitations. The main limitations in the analyses in all three chapters is the unavailability of information to distinguish between pre-planned and opportunistic stops in activity-travel chains. This information can help in the correct identification of the relationship between primary and secondary activities. Another limitation in Chapter 3 and Chapter 4 pertains to the dataset obtained from the four MPOs that has a large number of unavailable data on multi-day trips. As a result, the assumption of including all possible activity-travel chains in the study area becomes weak. One of the main limitations of Chapter 4 is the inability to estimate coefficients for both workers and non-workers using multi-group SEM. This limitation arises due to the differences in the set of predictors for workers and non-workers and thus restricts direct comparison of the strengths of the coefficients between these two groups. Finally, in Chapter 5, I used ride-hailing app usage frequency in the last 30 days to extract ride-hailing users from the combined category ride-hailing/taxi provided by NHTS. Availability of separate category for ride-hailing mode choice would ensure more reliability in the model estimates.

My dissertation unravels several intricate interactions between activity-travel chaining, socio-economic, activity-travel and land use attributes. But the complex nature of human travel behavior always provides avenues for further research. Future research on activity-travel chaining can incorporate the travel-related interactions among household members in allocating activities for activity-travel chaining. In such cases, it will be interesting to see, particularly for Chapter 4, how activity-travel chaining pattern of one member affects the activity-travel chaining pattern of another member. Another important area of study would be to investigate how the PMT impacts of activity-travel chaining translates to VMT, which is a very important criteria in travel demand forecasts.

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