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UNIVERSITY OF MINNESOTA

Smartphone-Based Interventions for Sustainable Travel Behavior: The University of Minnesota Parking Contract Holder Study

Final Report

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CTS 20-13

Technical Report Documentation Page

1. Report No.	2.	3. Recipients Accession No.
CTS 20-13		

4. Title and Subtitle
Smartphone-Based Interventions for Sustainable Travel Behavior: The University of Minnesota Parking Contract Holder Study

5. Report Date
October 2020

6.

7. Author(s)
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8. Performing Organization Report No.

9. Performing Organization Name and Address
Humphrey School of Public Affairs
University of Minnesota
301 19th Ave S, Minneapolis, MN 55455

10. Project/Task/Work Unit No.
CTS #2017052

11. Contract (C) or Grant (G) No.

12. Sponsoring Organization Name and Address
Center for Transportation Studies
University of Minnesota
440 University Office Plaza
511 Washington Ave. SE
Minneapolis, MN 55455

13. Type of Report and Period Covered
Final Report

14. Sponsoring Agency Code

15. Supplementary Notes
http://www.cts.umn.edu/Publications/ResearchReports/

16. Abstract (Limit: 250 words)
Innovative mobility apps have the power to transform the relationship between transportation networks and travelers. Capitalizing on the recent advancement in smartphone technology, this project develops a smartphone-based behavior intervention tool—named Daynamica—to provide customized, user-centered messages and graphics for promoting travel mode shifts from driving to more sustainable modes. The project tests the effectiveness of the intervention tool among University of Minnesota (UMN) parking contract holders. For each car trip made by a participant, the tool provides a mode shift plan based on the exact trip origin and destination. The tool also provides information describing the environmental impacts of the specific car trip and the personal benefits of switching to the alternative mode. The findings show that although 92 percent of participants are interested in trying alternative modes, in general, when it comes to specific trip considerations, only 36 percent of the car trips are considered reasonable alternative modes. There is ample interest among the most car-dependent population—parking contract holders—to explore alternative mode options; however, their interest is tempered by the limited alternative mode offerings in the region. Thus, it is recommended that transportation practitioners and policy makers improve these offerings. Furthermore, this research generates useful data to identify factors influencing mode shifting. Housing ownership, being male, making stops during the trip, and a late departure time for the morning commute are negatively associated with participants' receptiveness toward mode shifting. Finally, the report includes a novel analysis exploring the activity/trip chaining behaviors of the study participants.

17. Document Analysis/Descriptors
Travel behavior, commuters, smartphones, travel demand management, public transit, parking

18. Availability Statement
No restrictions. Document available from: National Technical Information Services, Alexandria, Virginia 22312

19. Security Class (this report)	20. Security Class (this page)	21. No. of Pages	22. Price
Unclassified	Unclassified	54	

SMARTPHONE-BASED INTERVENTIONS FOR SUSTAINABLE TRAVEL BEHAVIOR: THE UNIVERSITY OF MINNESOTA PARKING CONTRACT HOLDER STUDY

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OCTOBER 2020

Published by:

Center for Transportation Studies
University of Minnesota
440 University Office Plaza
2221 University Avenue S.E.
Minneapolis, MN 55414

This report represents the results of research conducted by the authors and does not necessarily represent the views or policies of the Center for Transportation Studies and/or the University of Minnesota and/or the University of Memphis. This report does not contain a standard or specified technique.

The authors, the Center for Transportation Studies, the University of Minnesota, and the University of Memphis do not endorse products or manufacturers. Trade or manufacturers' names appear herein solely because they are considered essential to this report.

ACKNOWLEDGMENTS

We wish to acknowledge those who made this research possible. The research was funded by the U.S. Department of Transportation's Congestion Mitigation and Air Quality (CMAQ) program. The research team was a sub-recipient of the federal CMAQ grant that the Twin Cities Metropolitan Council received. University of Minnesota Parking and Transportation Services provided significant help in recruiting study participants. Twin Cities Metro Transit provided matching funding to support this research.

EXECUTIVE SUMMARY

Innovative mobility apps have the power to transform the relationship between transportation networks and travelers. Capitalizing on the recent advancement in smartphone technology, this project develops a smartphone-based behavior intervention tool—named Daynamica—to provide customized, user-centered messages and graphics for the purpose of promoting travel mode shifts from driving toward more sustainable modes. The project tests the effectiveness of the smartphone travel behavior intervention tool among University of Minnesota (UMN) parking contract holders. One of the advantages of the tool is its ability to make more personalized recommendations based on actual daily travel behavior. For each car trip made by a participant, the tool provides information describing the environmental impacts of the specific car trip and the personal benefits of switching to alternative modes for the specific car trip. Participants are also presented with specific mode shift plans for each of the detected car trips based on the exact trip origin and destination. The findings show that although 92% of participants are interested in trying alternative modes, in general, when it comes to specific trip considerations, only 36 percent of the car trips are considered reasonable alternative modes. This finding shows that there is ample interest among the most car-dependent population—parking contract holders—to explore alternative mode options. However, their interest is tempered by limited alternative mode offerings in the region. Thus, it is recommended that transportation practitioners and policy makers improve public transportation offerings. Furthermore, beyond illustrating the usefulness of the smartphone-based travel behavior intervention tool, the research generates useful data to identify factors influencing mode shifting Housing ownership, being male, making stops during the trip, and a late departure time for the morning commute are negatively associated with participants' receptiveness toward alternative travel mode recommendations. Finally, the report includes a novel analysis exploring the activity/trip chaining behaviors of the study participants.

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CHAPTER 1: INTRODUCTION

The excessive use of privately owned, single-occupancy automobiles in the U.S. has contributed to a worsening energy crisis, environmental pollution, and traffic congestion; weakened economic productivity; and reduced quality of life. Research has shown that reducing the negative impact per car and per vehicle mile driven (e.g., via energy-efficient cars) does not sufficiently reduce the problems of car use (Steg, 2007). Behavior changes to reduce private automobile use among individual car users are needed to address the negative impacts of automobile dependence. Creating a balanced use of automobiles and alternative transportation modes (e.g., transit, biking, and walking) has the potential to maximize the health of people, environmental sustainability, and economic prosperity.

Research has shown that generic mass media intervention can be used in raising awareness of the benefits associated with alternative transportation modes (Ward, et al., 2007). However, critics question the effectiveness of generic information in bringing about sustained behavioral change. It is suggested that interventions closely tailored to individual needs may include less redundant information and are more likely to be read, saved, remembered, or discussed (Smeets, Brug, & de Vries, 2008). Evidence shows that respondents who receive individually tailored behavior promotion messages are more likely to change their behavior and maintain the changes following the intervention than respondents who receive generic information (Bock, Marcus, Pinto, & Forsyth, 2001).

However, developing a customized intervention program for promoting sustainable travel behavior can be challenging and doing so requires feedback and communication based on the participant's existing travel behavior. Issues involved in developing such programs include data collection of the participant's existing travel behavior, data transfer from the participant to the intervention implementer, and the timely communication of customized messages from the intervention implementer back to the participant.

Recent advances in mobile technology offer an attractive technical solution to these issues. The vast majority of Americans (about 96% of the total population) subscribe to a mobile network and 81% of Americans own a smartphone with advanced computing, communication, and sensing capabilities (Pew Research Center, 2020). Most smartphones on the market (e.g., Android, iPhone, Windows Mobile, and Blackberry) have built-in GPS and accelerometer sensors capable of tracking location changes, travel speed, travel mileage, and the intensity of physical activity. These advances, along with advanced computing and communication technologies embedded in these smartphones, have created opportunities for real-time communication of personalized travel behavior promotion messages as well as real-time assessment of the suggested travel behavior shift's environmental and health benefits (Fan, Chen, Liao, & Douma, 2012).

Capitalizing on the recent advancement in smartphone technology, this project develops a smartphone-based behavior intervention tool—named Daynamica—to provide customized, user-centered messages and graphics for the purpose of promoting travel mode shifts from driving to more sustainable modes. The project tests the effectiveness of the smartphone travel behavior intervention tool among University of Minnesota (UMN) parking contract holders. As one of the largest employers in the region, UMN has more than 15,000 employees who regularly use a car for their daily commute. According to the 2013 Longitudinal Employer Household Dynamics (LEHD) program, UMN employees come from cities across the region, including Minneapolis, St. Paul, Plymouth, Blaine, Woodbury, and Edina, to name a few. Reducing drive-alone rates to UMN can play an important role in decreasing carbon emissions and traffic congestion in the Twin Cities metropolitan region. UMN is also interested in improving the ease of commutes for community members to ensure it remains an attractive place to work and learn.

The research team collaborated with Metro Transit and University Parking and Transportation Services to test the smartphone-based travel behavior intervention tool. UMN parking contract holders were recruited with an email to UMN community members and through a UMN website. Participants were offered a $40 Go-To Card, Metro Transit fare media to explore commute alternatives, and a $40 gift card to Starbucks or Target for their participation in the study. To be eligible, participants must have driven to and parked on campus at least three times per week prior to the study. Participants were asked to carry a supplied phone with the Daynamica mobile app for two weeks, respond to a 5-minute demographic entry survey, respond to short automatically generated surveys about their trips (in the Daynamica app), check-in with a research team member after the first week, and return the supplied phone after the end of the two-week period. A total of 895 potential participants filled out the entry survey and consented to participate in the study. Due to limited study resources, including number of phones, only 300 participants were included. Overall, the study gathered data on 16,237 trips compromising 23,652 mode segments.

Beyond illustrating the usefulness of the smartphone-based travel behavior intervention tool, the research generates useful data to identify factors influencing mode shifting among the most car-dependent population—parking contract holders. The granular travel behavior data allows UMN to better understand the commuting needs of its employees. This information can assist University Parking and Transportation Services manage parking availability. We investigate what characteristics can limit mode switching, such as lack of knowledge or the need to make a stop on the way to or from work, and what characteristics can encourage mode switching, such as one's work arrival time or proximity to work. An employee's willingness to use alternative modes to single-occupant vehicle (SOV) commuting will greatly impact decisions to expand or decrease current parking availability on campus.

Lastly, this report constructs activity chains in an attempt to describe activity sequencing of the study's population. We propose a methodology for creating activity chains and provide two opportunities for analysis: differences among gender and differences between week days and weekend days. Our hope is to generate a discussion on how to create and use activity chain information in the study of travel behavior.

The organization of the report is below:

Chapter 2 details the study design and data collection methods. It describes the development of the Daynamica app—the smartphone intervention tool. Daynamica automatically registers activity and travel patterns, then promotes mode shift recommendations for similar trips. Furthermore, surveys written into the app measure whether participants are interested or willing to consider an alternative trip mode.

Chapter 3 details the intake survey responses and study participant characteristics. Descriptive statistics for the intake survey respondents and for the final study participants show gender imbalance in the study sample. More than two-thirds of the intake survey respondents identify as female.

Chapter 4 presents the daily activity-travel behavior data collected for all enrolled participants. Overall, a total of 3,318 days of valid activity-travel behavior data are collected from the 300 participants, resulting in an average of about 11.1 days of activity-travel behavior data per participant. This chapter breaks down the average frequency and duration of activities and the average frequency, duration, and distance of trips. Trips are examined by both trip mode and trip purpose.

Chapter 5 describes the results of participant reactions to alternative trip recommendations during the Phase 2 Intervention. Phase 2 of the study implemented a two-question survey that asked participants to rate whether each alternative mode recommendation they received was reasonable, and whether they would ever consider trying that recommendation. The participants in Phase 2 completed 1,309 surveys, about 35 surveys per participant. We then examined differences in the response to recommendations among trip types and participant characteristics.

Chapter 6 details the analysis of the alternative trips recommended to participants in the Phase 2 Intervention group. The analysis compares the trip duration of the actual completed trip to the recommended trip and how the difference could impact survey responses analyzed in Chapter 5. The Daynamica app generated 139 Park & Ride trip recommendations and 317 Transit trip recommendations.

Chapter 7 presents the activity chaining methodology to characterize the activity patterns of all enrolled participants in the study. Activity chain data is constructed by grouping a participant’s data on a per day basis. Each day is then illustrated as a list of simplified activities to provide a general idea of what a person did that day. Activity chains are then compared between men and women in the study and between weekdays and weekends.

Finally, Chapter 8 discusses the primary results and takeaways of this report.

CHAPTER 2: STUDY DESIGN AND DATA COLLECTION

This study aims to reduce traffic congestion and greenhouse gas emissions by promoting travel mode shifts among car commuters from driving to more sustainable modes. The study uses a smartphone-based behavior intervention application to promote mode shifting. The smartphone app is designed to collect each participant's daily travel behavior patterns, make alternative mode suggestions for each car trip made by the participant, and provide instantaneous comparison regarding trip time, cost, carbon footprint, and physical activity benefits between single-occupant driving and the alternative options.

This study demonstrates the effectiveness of the behavior intervention app by recruiting regular University of Minnesota (UMN) car commuters to use the tool and collect relevant data. The study involves two phases of data collection; staff transitions and an interim data analysis required a second phase of recruitment. The initial intervention group failed to receive information on the alternative mode suggestions and their potential benefits of shifting driving to these alternative modes. In Phase 2, the study design shifted from a randomized controlled trial to a non-randomized trial with a slightly modified intervention to ensure that the participants review the alternative mode information and provide feedback on how useful the information is for encouraging modal shifts. The details of the study design and two-phased data collection efforts are described below.

2.1 STUDY POPULATION AND RECRUITMENT

Our targeted population is individuals who work at and drive to UMN Twin Cities campus at least three days per week. As one of the largest employers in the Twin Cities region, UMN has more than 15,000 employees who regularly use a car for their daily commute. At the end of the 2019 school year (June), there were 9,491 assigned staff and faculty parking contracts (PTS, 2019). A 2016 survey found that approximately 29 percent of staff and faculty primarily drive alone to work (PTS, 2019). UMN observed a steady decline in the drive alone rate since 2010 while the total number of cars parked annually has slightly increased; the total sales of the Metropass among staff and faculty has remained stagnant since 2010 (PTS, 2019). According to the 2013 Longitudinal Employer Household Dynamics (LEHD) database, UMN employees come from cities across the region, including Minneapolis, St. Paul, Plymouth, Blaine, Woodbury, and Edina.

The study reached out to potential participants through email. The Parking and Transportation Services (PTS) at UMN maintains a database of parking contract customers on their campuses. PTS sent the following email to the employee parking contract customers at the Twin Cities campus in February 2018 to recruit potential participants into the study.

> Subject: Participate in Commuting Research Study
>
> Making commutes to campus easier is an important part of continuously serving the University community. Whether a person drives, rides mass transit, or uses any other form of transportation, having the best information on transportation options is beneficial to all.

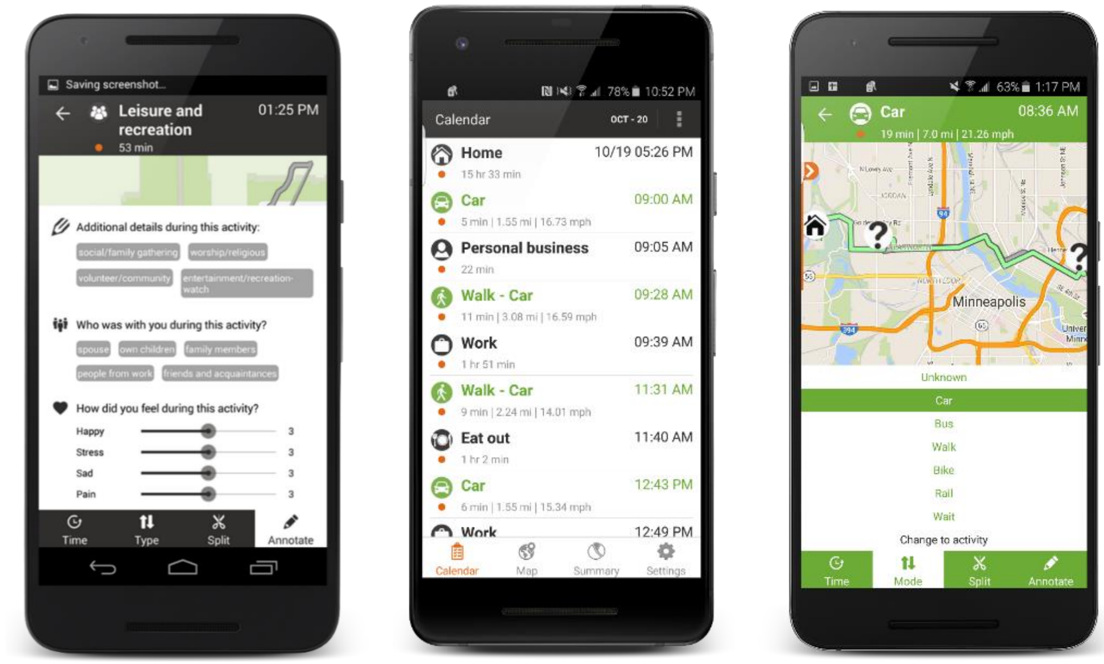
A team of University researchers is working with the Metropolitan Council--who coordinate transportation planning for the Twin Cities region--to do just that. Planning for easier commutes depends on detailed information about how people commute. That's where you come in:

You are invited to participate in this research by carrying a smartphone loaded with Daynamica--a special app developed by U of M researchers to easily collect data on the trips you make throughout your day. Your individual data will not be shared with anyone outside the research team. As a thanks for your time, you'll receive up to $40 in Starbucks or Target gift cards, as well as a $40 transit card to explore travel alternatives.

If you're interested, you can visit top.umn.edu for more details and to sign up, or email Andrew Guthrie, project manager for the Travel Options Project at top@umn.edu with any questions you may have.

2.2 THE DAYNAMICA APP

The Daynamica app (formerly SmarTrAC) was initially developed in 2013–2015 by Dr. Fan and her collaborators under contract with the U.S. Department of Transportation in support of the Intelligent Transportation Systems Joint Program Office's Dynamic Mobility Application program (Fan et al., 2015). It integrates the sensing, data mining, and surveying capabilities of the smartphone to collect human activity and travel behavior data with minimal user burden, increased accuracy, and allowing for contextual questions and prompts (US Patent No. US9763055B2). Figure 1 shows the main interface of the Daynamica app.



Daynamica automatically constructs sequenced activity and travel episodes throughout the day.

Daynamica enables users to correct auto-constructed activity and travel episodes if needed.

Daynamica enables customized surveys for additional user inputs on activity and trip episodes.

Figure 1: Daynamica Main Interface

The basic functionality of the Daynamica app is for users to go about their daily activities as the app automatically collects data on their activities and trips. Occasionally, the user may open the app to edit or confirm the data collected. Edits could involve modifications to the activity/trip type classification as well as to the start and end time of the event. As a result, the app collects both continuous and momentary information about people's activity-trip behavior:

- It collects and processes location and motion sensing data in real time to automatically construct a timeline of activity and trip episodes in the present day.
  It enables users to provide information on each constructed episode after it has concluded, including information on emotional experiences.

Following its initial development, the Daynamica app has been deployed in multiple research studies ranging from travel behavior research in urban planning to physical activity and emotional well-being research in public health. In this project, the Daynamica app is augmented with behavior intervention functions. The augmented design of the Daynamica app follows the Integrated Change Model (i.e., I-

Change), which integrates three phases in the behavioral change process: awareness, motivation, and action (de Vries, et al., 2003).

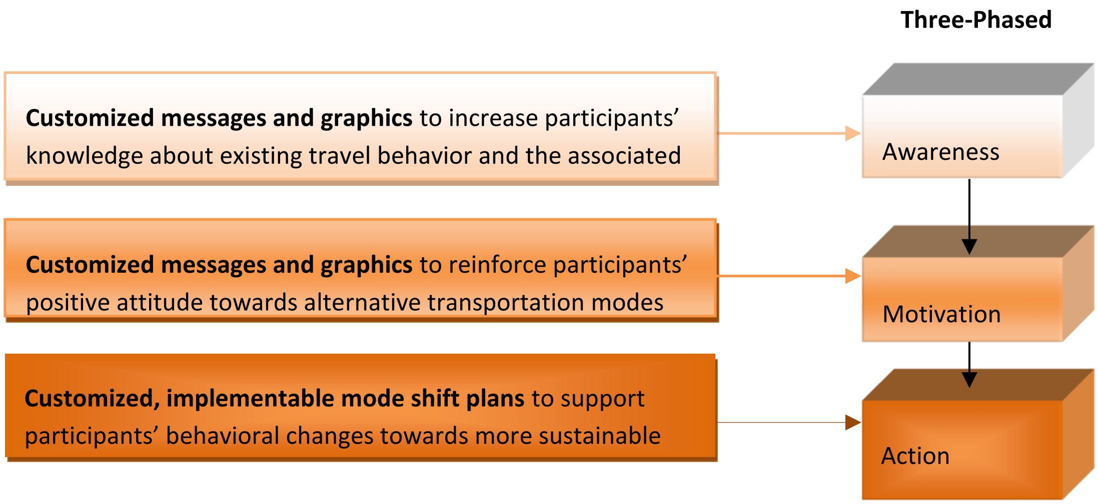


Figure 2: Smartphone-Based Tool for Travel Behavior Changes: Application of the I-Change Model

As illustrated in Figure 2, the first phase is awareness. The Daynamica app accomplishes awareness by providing customized messages and graphics based upon the user's existing travel behavior; messages describing environmental impacts associated with each driving trip (e.g., carbon emissions) are displayed to the user. In the motivation phase, messages are customized to reinforce the perceived positive aspects of transit and non-motorized travel and to address perceived barriers; messages describing personal benefits of a mode shift (e.g., cost savings and health benefits) are displayed. In the action phase, the smartphone tool provides participant with specific, implementable action plans on how to shift from driving to taking transit and/or walking/biking for their daily trips. Specifically, if a driving trip is made from the user's home to a grocery store, based upon the detected trip origin and destination, the smartphone tool uses existing transit routing services (e.g., Google Map) to provide information on which transit stops and routes to use and how long the trip would take for the same origin-destination pair.

We added new functions to the Daynamica app to provide the alternative travel mode recommendations for confirmed trips that involve car segments. Figure 3 depicts the information associated with each mode recommendation shown to the users on their smartphone. The information includes the environmental footprints of the actual car trip and the suggested mode (awareness), the positive aspects of taking the suggested mode such as reduced costs and carbon emissions and increased productivity (motivation), and how use the suggested mode to make the same trip.

Note that trips can be multimodal. For example, people often need to walk to the parking lot and then drive to the destination. For each confirmed trip that involves a car segment, the Daynamica app is designed to provide alternative mode recommendations based upon the trip origin and destination (i.e., the starting and ending points of the entire trip) rather than the starting and ending points of the car segment in the trip. This was done to improve reasonableness of the alternative mode recommendations because one would prefer a bus that drops them close to the actual trip destination rather than where they usually park the car.

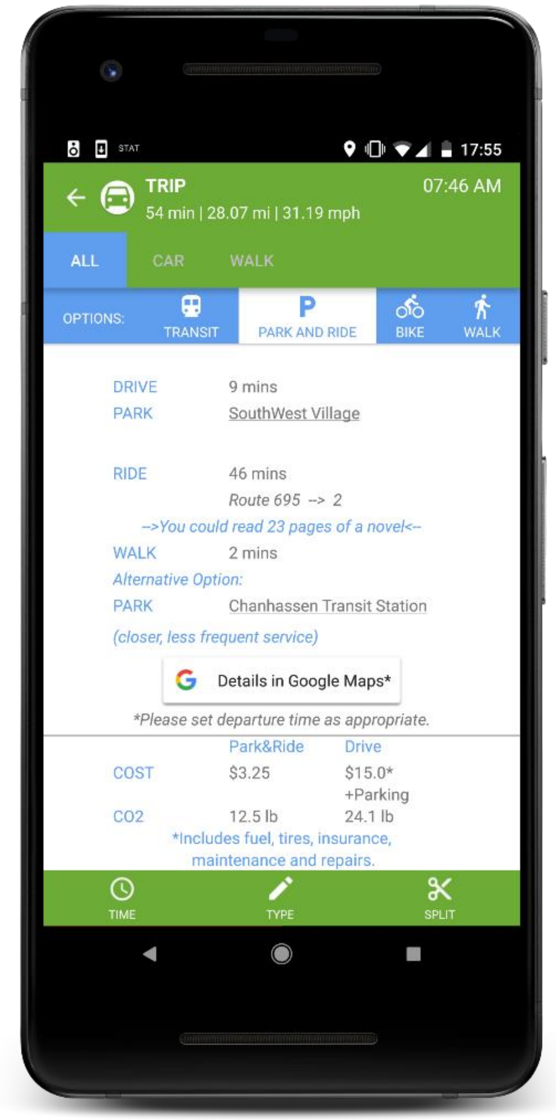


Figure 3: Alternative Mode Recommendations in Daynamica

Four different alternative travel mode recommendations are provided for each car-involved trip: Transit, Park and Ride, Bike, and Walk:

The transit mode recommendation is essentially a walk-and-ride transit option; in Google Maps Directions API, the default access and egress mode to get to/from the transit stop is walking. The transit recommendations are based on the trip origin, trip destination, the trip departure time, and the day of the week. The use of temporal information for deriving transit mode recommendations is necessary because transit services are time-dynamic. It is important to ensure that transit services are available not only for connecting the trip origin and destination in the spatial dimension, but also at the time of the day and during the day of the week that the participant likely makes the same trip. Given that our study participants were parking contract holders who were likely car-dependent, we only provide the transit options suggested by Google Maps that 1) involved no or at most one transfer; and 2) the one-way walk time to the transit stop or from the transit stop is less than 20 minutes.

The park-and-ride mode recommendation integrates Google Maps Directions API with information from transit agencies on the locations of park and ride facilities and the frequencies of park and ride services. Based on origin and destination locations, the recommendation automatically presents a drive-transit-walk option if the trip destination is in either downtown or on the UMN campus; or a walk-transit-drive option if the trip origin is in either downtown or on the UMN campus. The recommendation (shown in Figure 3) includes the name and location of the recommend park and ride facility; the travel time associated with the access, on-board, and egress segments; and the costs and carbon emissions compared with the driving scenario. In 2018, Google Maps provided the walk-and-ride transit option only; the automated park and ride trip planning is a unique feature of the Daynamica app developed for the smartphone tool. Our recommended park-and-ride options include options tailored to user preferences (e.g., the user could ask for a park and ride facility that is closer to home or a facility that provides more frequent transit services).

Unlike the transit and park-and-ride recommendations, biking and walking recommendations did not involve temporal information such as trip start time because biking and walking are not limited by the time availability of certain services. The biking and walking recommendations did include information on how biking and walking reduced travel costs and carbon emissions in comparison with the driving scenario, similar to the other mode recommendations. In addition, the recommendations include how biking and walking have physical activity benefits measured by calories burned.

To improve communication of benefits associated with potential modal shift for a specific car trip, we made efforts in three aspects of the user interface design:

- Clarity and layout: building a graphically-aided description of the benefits from using an alternative mode so that the information on the benefits can be absorbed and understood at a glance;
- Examples of mode-shift benefits: providing real-world examples of the benefits of shifting to other modes, e.g. how many pages of a book one could read.
- Highlights of multiple benefits: the benefits include improving environmental sustainability by saving CO_2 emissions; reducing travel costs; and increasing physical activity.

The following equations were used to calculate potential mode-shift benefits:

- The estimated travel cost by car = \$0.535 x Miles Travel by Car.
- The estimated carbon dioxide emission for a trip by car = 0.86 lb. of CO_2 x Miles Travel by Car.
- The estimated travel cost by bus = \$2.5, a rush hour fare on local bus or METRO service.
- The estimated carbon dioxide emission for a trip by bus = 0.48 lb. CO_2 x Miles Travel by Bus.
- The estimate travel cost for a Park & Ride trip = \$3.25 + (\$0.535 x Miles Travel by Car). An express bus fare is \$3.25.
- The estimated carbon dioxide emission for a Park & Ride trip = (0.86 lb. of CO_2 x Miles Travel by Car) + (0.48 lb. of CO_2 x Miles Travel by Bus), the sum of the estimated emission from both the Car and Bus.
- For trips that involve public transit segments, the estimate number of pages read onboard = Transit Segment Duration in Minutes ÷ 2, assuming an average of 2 pages read per minute.
- For walking and biking modes, the estimated calories burned during the trip = (Mode Segment Duration in Minutes x 24) ÷ 4.

- For walking and biking modes, the estimated percentage of physical activity per day = (Walking or Biking Segment Duration in Minutes ÷ 21.43) x 100. The percentage is based on the recommended 150 minutes of physical activity per week.

2.3 TWO-PHASED DATA COLLECTION

The data collection efforts for this study involved two phases:

- The Phase 1 data collection efforts began in March 2018 and ended in September 2018, which featured a randomized controlled trial with a failed intervention, including 263 participants.
- The Phase 2 data collection efforts began in late November 2018 and ended in May 2019, which featured a non-randomized single arm study in which all participants received intervention and answered two trip-based surveys on how effective they think the intervention is. Phase 2 data collection included 37 participants.

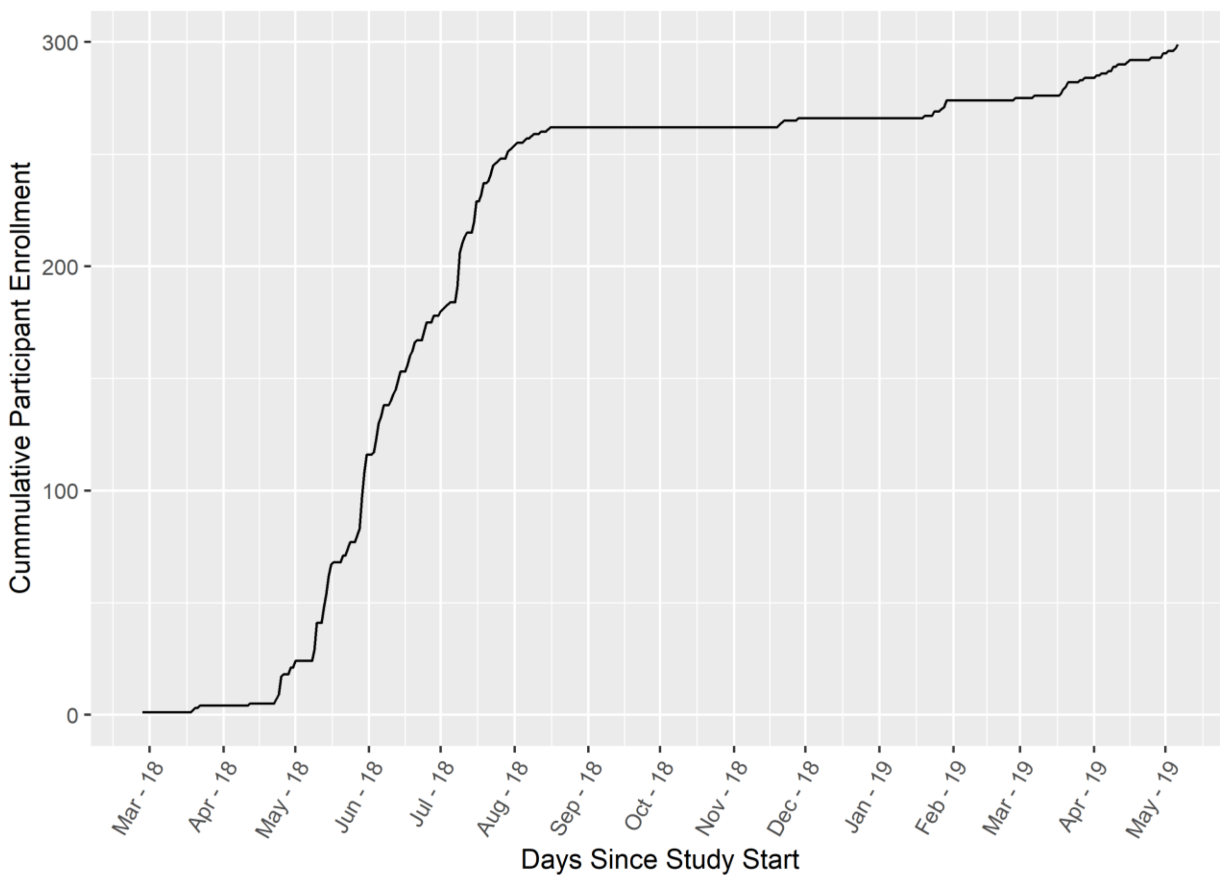


Figure 4: Cumulative Participant Enrollment

The Phase 1 efforts enrolled 263 participants. These participants were randomized into control and intervention groups with a 1:1 allocation ratio. Both groups were provided with an android smart phone with the Daynamica smartphone application. The applications installed were different for the control and intervention groups:

- The control group participants received a LG phone on which the Daynamica app only collects travel behavior data without any functions for promoting modal shift.
- The intervention group participants received a LG phone on which the Daynamica app has the extended functionality of making alternative mode recommendations for any car-involved trips (as shown in Figure 3).

Both control and intervention participants were expected to keep the LG phone with them throughout the day for 14 consecutive days. Study compliance was measured through app usage where participants were asked to confirm the trips and activities that the app automatically recorded. Confirmation included updating the trip mode (Car, Bus, Walk, etc.) and activity type (Home, Work, Leisure & Recreation, etc.) as well as start or end times as necessary. Participants were expected to aim for a confirmation percentage for trips and activities of 90%.

Both control and intervention participants receive the following compensations:

- A $40 Go-To Pass Card was provided at the time that the student research assistant dropped off the LG phone with the participant on campus to begin the 14-day data collection. The $40 Go-To Pass allowed parking contract holders to utilize public transportation options without concerns to the cost; they will not be penalized by not using their prepaid contract and taking transit.
- A $20 Starbucks or Target Gift Card (based upon participant preference) was provided one week into the 14-day data collection process when the student research assistant conducted the interim check-in with the participant on campus. During the one-week check in, the student research assistant reviewed app functionality and verified trip confirmation percentages with the participant.
- A $20 Starbucks or Target Gift Card was provided at the end of the 14-day data collection and when the student research assistant retrieved the phone from the participant on campus and under the condition that the participant met the minimum participation requirement (i.e., 90% activity/trip confirmation).

In August 2018, there was a pause in data collection to review study progress and examine the quality of the collected data. The preliminary analysis with data collected between March–August 2018 showed that the study participants were not receiving the intervention options as frequently as we predicted. Many intervention group participants were unaware that recommendations were even being provided; in addition, it was difficult for the research team to ascertain who was looking at recommendations and who was not. Because of the lack of data collected on recommendations in the first phase of the study, a second phase was planned to focus on questions directed to the participants to understand the quality of the recommendations provided.

These directed questions, in the form of surveys, also allowed study workers to quickly learn who was viewing the recommendations and who may need assistance in accessing that feature within the app. Recommendations were provided on a per request basis. This meant the participant had to actively ask for recommendations; the app would not prompt the user with a notification if a recommendation was available to view. When asking for a recommendation within the app, participants are able to ask for a recommendation of only a single travel mode. For example, for a given trip, a participant may opt to only receive the Park and Ride recommendation; in this case, the Transit recommendation would not be provided. This method was used to limit the data and battery usage on the phone.

Given the concerns about Phase 1 data collection, the study began Phase 2 data collection efforts in February 2019. In Phase 2, all participants were enrolled into the intervention group, effectively switching the study from a randomized controlled trial to a non-randomized single arm study. To ensure that the Phase 2 participants receive the intervention (i.e., review the alternative mode recommendations associated with each car-involved trip that the participant made), a trip-based survey feature was added to the Daynamica app. This survey feature (as shown in Figure 5) asks for feedback from each study participant on trip recommendations, which prompts the participant to look at the recommendations and indicate how appealing each of trip recommendation is. The participants are required to fill out at least 75% of these surveys to receive study compensation.

Phase 2 data collection only included 37 participants due to time, resource, and financial constraints.

Aside from the trip-based surveys asking the participants to identify which alternative travel mode recommendations were reasonable and which they would consider trying in the future, there were no differences in the intervention version of the application used between Phase 1 and Phase 2.

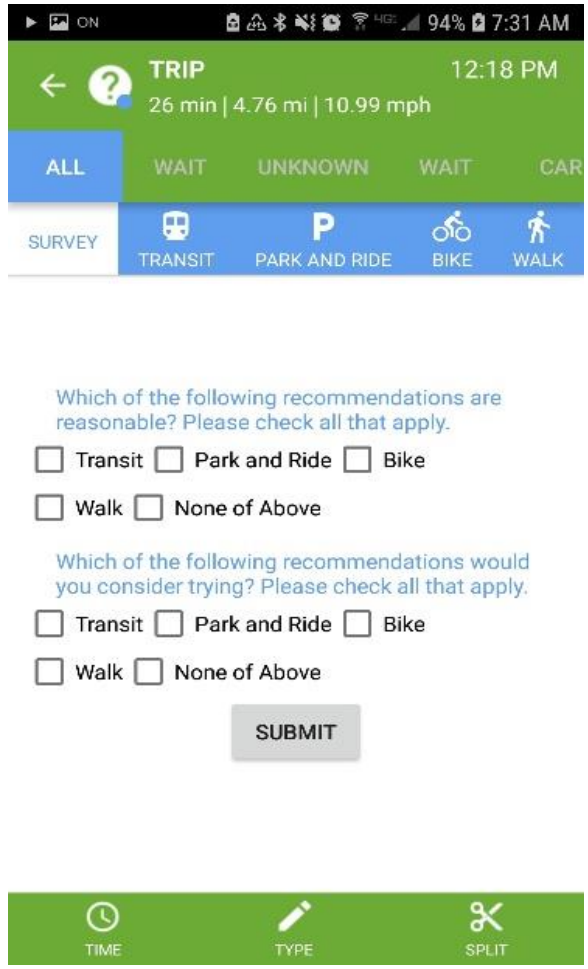


Figure 5: Trip-Based Survey on Alternative Mode Recommendations in Phase 2

CHAPTER 3: INTAKE SURVEY AND ENROLLED PARTICIPANT DATA

In the email sent by the UMN Parking and Transportation Services, interested UMN car commuters were asked to fill out the intake survey on the study website at top.umn.edu. A total of 817 people completed the intake survey and consented to participate in the study. The intake survey begins with eligibility questions: “Do you wish to participate?” and “Do you normally drive to campus at least 3 days a week?”, followed by questions on parking locations, personal socio-demographics, family structure, and typical commute behavior.

Of the 817 respondents who signed up for the study, the project team was only able to enroll 300 participants into the study due to limited staffing and funding resources. Table 1 summarizes the descriptive statistics of the 817 intake survey respondents, the 300 Enrolled Study participants (including participants in both Phases 1 and 2 data collection efforts), and the 37 Phase 2 Intervention participants. The Phase 2 Intervention ensured that all participants actually received the intervention. The sample characteristics are relatively similar between Intake Survey participants, Enrolled Study participants in general, and the Phase 2 participants.

All variables in Table 1 are categorical variables except age. The categorical variables are tabulated and the count (N) and percentage (%) are presented for each level in the categorical variable. For the continuous variable, age, the mean and standard deviation are presented.

Table 1: Descriptive Statistics of the Intake Survey and Enrolled Participant Samples

	Intake Survey Respondents	Enrolled Study Participants	Phase 2 Intervention Participants
Sample Size: N	817	300	37
Employee Type: N (%)			
Faculty	86 (10.5)	26 (8.7)	2 (5.4)
Hourly staff	278 (34.0)	105 (35.0)	10 (27.0)
P & A Staff	320 (39.2)	124(41.3)	17 (45.9)
Other Staff	119 (14.6)	41(13.7)	7 (18.9)
Student	14 (1.7)	4(1.3)	1 (2.7)
Campus Location: N (%)			
East Bank	685 (83.8)	253 (84.3)	30 (81.1)
St. Paul	7 (0.9)	3 (1.0)	1 (2.7)
West Bank	125 (15.3)	44 (14.7)	6 (16.2)
Gender: N (%)			
Female	637 (78.0)	231 (77.0)	29 (78.4)
Male	174 (21.3)	68 (22.7)	8 (21.6)
Other	5 (0.6)	1 (0.3)	0 (0.0)
Race and Ethnicity: N (%)			
White	695 (85.1)	262 (87.3)	33 (89.2)
Black	44 (5.4)	13 (4.3)	1 (2.7)

	Intake Survey Respondents	Enrolled Study Participants	Phase 2 Intervention Participants
Hispanic	22 (2.7)	5 (1.7)	0 (0.0)
Other	25 (3.1)	6 (2.0)	0 (0.0)
Household Structure: N (%)			
Living w no one	113 (13.8)	46 (15.3)	6 (16.2)
Living w Spouse/Partner	568 (69.5)	209 (69.7)	26 (70.3)
Living w 0-5 yrs old	181 (22.2)	66 (22.0)	10 (27.0)
Living w 6-17 yrs old	222 (27.2)	88 (29.3)	12 (32.4)
Living w Other	110 (13.5)	39 (13.0)	6 (16.2)
Household Income: N (%)			
$25,000 - $35,000	12 (1.5)	5 (1.7)	0 (0.0)
$35,000 - $50,000	63 (7.7)	26 (8.7)	2 (6.2)
$50,000 - $75,000	128 (15.7)	49 (16.3)	8 (25.0)
$75,000 - $100,000	173 (21.2)	55 (18.3)	6 (18.8)
More than 100,000	384 (47.0)	151 (50.3)	16 (50.0)
Car Burden: N (%)			
No burden at all	112 (13.7)	45 (15.0)	2 (5.4)
A small burden	413 (50.6)	163 (54.3)	27 (73.0)
Something of a burden	250 (30.6)	85 (28.3)	8 (21.6)
A large burden	38 (4.7)	6 (2.0)	0 (0.0)
Making Stops During the Commute Trip: N (%)			
Never	68 (8.3)	16 (5.3)	2 (5.4)
Rarely	199 (24.5)	78 (26.0)	3 (8.1)
Sometimes	270 (33.0)	110 (36.7)	17 (45.9)
Often	144 (17.6)	51 (17.0)	9 (24.3)
Always	134 (16.4)	45 (15.0)	6 (16.2)
Used Transit Before: N (%)	501 (61.3)	170 (57.7)	27 (73.0)
Used Park & Ride Before: N (%)	254 (31.1)	96 (32.0)	16 (43.2)
Parking Contract Holder: N (%)	795 (97.3)	298 (99.3)	37 (100.0)
Interested in Alternative Modes: N (%)	707 (86.5)	260 (86.7)	34 (91.9)
Own Housing: N (%)	607 (74.3)	235 (78.3)	28 (75.7)
Age: Mean (SD)	44.07 (12.35)	45.03 (12.66)	45.38 (9.61)

The 300 study participants represent a variety of employee types at UMN and included a few students. Most participants were located on the East Bank campus; 84.3 percent of the participants were based there. Only a handful of participants were located in St. Paul. This is not surprising; the PTS first sent the recruitment email to parking contract holders on the East Bank campus.

The study participants were predominantly female (77.0%), indicating strong gender imbalance in the study sample. Future studies may deliberately recruit equal number of female and male participants to avoid gender bias. The study participants were also predominately white (87.3%) reflecting the racial distribution in the Minneapolis-St. Paul metropolitan region and among car commuters to a higher education institution. The majority of the participants (50.3%) had a combined household income over $100,000, which is much higher than the median household income of $76,856 in the Minneapolis-St. Paul metropolitan region. Further, the majority of the study participants lived with a spouse and/or partner and over half lived with children; this is true for both the Enrolled Study participants and the Phase 2 participants.

The majority of the study participants (68.7%) at least sometimes made stops on their way to work, such as to drop children off at school or go to the grocery store. Over half (57.7%) had used transit modes before, about a third (32.0%) used Park and Ride facilities before, and a large majority (86.7%) were interested alternative modes. Only 2 percent of the study participants reported that owning a car was a large burden; the majority of participants (54.3%) reported it being a small burden; 15 percent reported it being no burden at all; while over a fifth (28.3%) reported it being something a burden.

CHAPTER 4: SMARTPHONE-BASED ACTIVITY-TRIP DATA

This chapter focuses on describing the daily activity-trip behavior data collected with the Daynamica app from the enrolled participants. Overall, a total of 4,442 days of activity-trip behavior data were collected from the 300 participants. Due to many factors such as phones running out of battery, abnormal app use causing the app to crash, and weak GPS signal, not all days have complete activity-trip behavior data throughout the 24 hours. Table 2 summarizes the number of days with complete and partial data.

Of all the days with any data, 55.6 percent have the complete 24 hours of data; 66 percent have more than 23 hours of data; 76.7 percent have more than 16 hours of data; and 94.2 percent have more than 8 hours of data. The number of weekend days with at least 8 hours of data (474 Saturdays and 426 Sundays) is lower than the number of weekdays (ranging from 610 to 682 across weekdays).

Table 2: Completeness of the activity-travel behavior data by the day of the week

Day of the Week	# of days with full 24 hours of data	# of days with more than 23 hours of data	# of days with more than 16 hours of data	# of days with more than 8 hours of data	Total # of days
Monday	329 (50.6%)	408 (62.8%)	492 (75.7%)	610 (93.8%)	650
Tuesday	390 (55.9%)	451 (64.6%)	537 (76.9%)	656 (93.9%)	698
Wednesday	392 (55.3%)	464 (65.4%)	536 (75.6%)	668 (94.2%)	709
Thursday	393 (54.6%)	468 (65.0%)	540 (75.0%)	682 (94.7%)	720
Friday	386 (55.8%)	459 (66.3%)	527 (76.2%)	667 (96.4%)	692
Saturday	310 (61.8%)	371 (73.9%)	424 (84.5%)	474 (94.4%)	502
Sunday	271 (57.5%)	311 (66.0%)	351 (74.5%)	426 (90.4%)	471
Total	2471 (55.6%)	2,932 (66.0%)	3,407 (76.7%)	4,183 (94.2%)	4,442

In this report, we define a valid activity-trip day as a day with more than 16 hours of data. The remainder of the chapter focuses on summarizing activity and trip statistics using the data associated with the 3,407 valid activity-trip days.

4.1 ACTIVITIES

Table 3 summarizes the activity data collected with the Daynamica app. The activity frequency and duration summarization in Table 3 includes the valid activity-trip days only. The total amount of time spent on activities is approximately 21 hours per day. The remaining three hours is either time spent on trips (see summary statistics in the next section) or missing data.

For Home activities, people recorded an average 2.13 activities per day on weekdays and 2.33 activities per day on weekends. This indicates an increase in the number of times a participant departs and enters their home during the weekend. For Work activities, people recorded an average 1.64 activities per day on weekdays but only 0.10 activities per day on weekends, indicating a predominant Monday–Friday work schedule among the study participants.

On weekends, we see major increases in the number and duration of Shopping and Leisure & Recreation activity types compared to weekdays but do not see major increases for Personal Business and Eating Out activity types. Overall, the total number of activities during a day doesn't change noticeably from weekday to weekend. The majority of the participants' time was spent at Home or Work. Between weekdays and weekends, participants spent 56 percent and 71.9 percent of their time at Home. During weekdays, participants spent 32.7 percent of their time at Work. Figure 6 shows the distribution of activities for all days combined, weekdays, and weekends.

Table 3: Average activity frequency and duration per person per day by the activity type among the days with more than 16 hours of Daynamica app data

Activity Type	Number of Activities per Person per Day (%)			Activity Hours per Person per Day (%)		
	Weekday	Weekend	All Activities	Weekday	Weekend	All Activities
Home	2.13 (34.8)	2.33 (39.0)	2.18 (35.9)	12.08 (56.0)	15.65 (71.9)	12.89 (59.6)
Work	1.64 (26.8)	0.10 (1.7)	1.29 (21.2)	7.05 (32.7)	0.43 (2.0)	5.55 (25.6)
Education	0.06 (1.0)	0.02 (0.3)	0.05 (0.8)	0.12 (0.6)	0.05 (0.2)	0.10 (0.5)
Shop	0.43 (7.0)	0.97 (16.2)	0.55 (9.0)	0.26 (1.2)	0.60 (2.8)	0.34 (1.6)
Eat Out	0.30 (4.9)	0.45 (7.5)	0.33 (5.4)	0.24 (1.1)	0.48 (2.2)	0.29 (1.3)
Personal Business	0.63 (10.3)	0.57 (9.5)	0.62 (10.2)	0.64 (3.0)	1.07 (4.9)	0.74 (3.4)
Leisure & Recreation	0.36 (5.9)	1.01 (16.9)	0.51 (8.4)	0.70 (3.2)	2.61 (12.0)	1.14 (5.3)
Other	0.55 (9.0)	0.51 (8.5)	0.54 (8.9)	0.50 (2.3)	0.89 (4.1)	0.59 (2.7)
Total	6.115 (100)	5.98 (100)	6.08 (100)	21.59 (100)	21.78 (100)	21.64 (100)

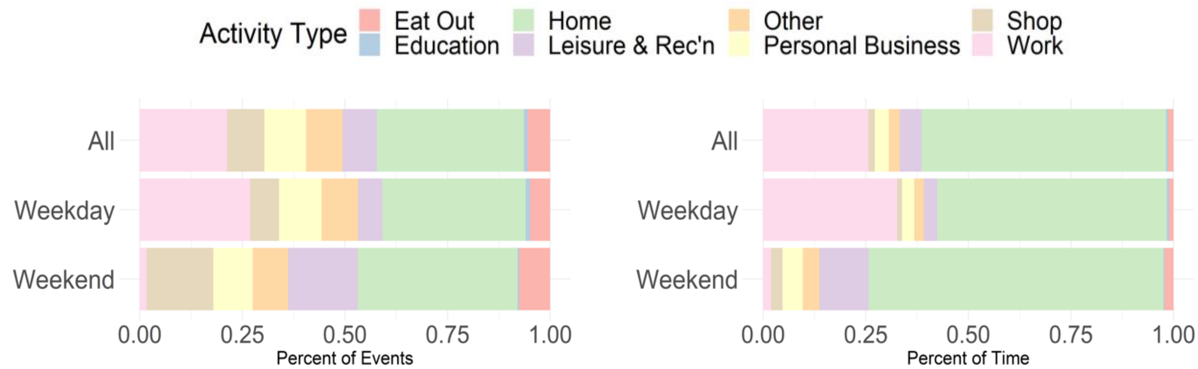


Figure 6: Percentage Breakdowns of Events Counts and Time Spent Engaged in Activites During the Day

4.2 TRIPS

The Daynamica app defines a trip as the movement between the previous activity location and the next activity location. Following the activity-trip separation algorithm embedded in the Daynamica app, the previous activity location (trip origin) and the next activity location (trip destination) must be more than 200 meters apart from each other. A trip may include multiple travel mode segments (e.g., walking and driving). If a trip involves multiple modes, the mode associated with the longest travel distance during this trip is defined as the primary mode of the trip. For example, if a trip involves one mile of driving and 0.5 miles of walking, driving is the primary mode of this trip. Using this trip and primary mode definition, our data collection efforts from the 300 enrolled participants generated 16,845 complete trips, including 77.6 percent with car as the primary mode and 19.8 percent with walking as the primary mode (Table 4).

Table 4 and the associated figure below show summary information about trips as classified by their primary mode. The majority of trips per day (77.6%) used cars as their primary mode. This was consistent for weekday and weekend trips, but weekend trips had a higher proportion than weekday trips (87.9% vs 74.6%). The number of trips per day spent biking is dramatically higher on weekends at 11 percent of trips per day compared to one percent of trips per day during weekdays. Across all days, an average 0.98 walking trips per day were recorded. Walking trips dropped by about half between weekdays and weekends (1.13 to 0.47), a finding which may be due to the fact that, as university workers, study participants might frequently walk between buildings on campus. The time spent walking during weekdays is higher than during the weekends, while the time spent in the car increases on weekends as compared to weekdays.

Note that the travel duration and distance calculations in Table 4 are based on primary modes, not the mode segments. The primary mode is a composite measure of a trip potentially containing multiple mode segments with a single mode designated as the primary; the travel duration and distance calculations by the primary mode of a trip represent the mileage and duration for the trip and do not represent the mileage and minutes associated with the primary mode used in the trip. If you're interested in the actual distance and duration associated with individual travel modes, see Table 6.

Table 4: Average trip frequency, duration, and distance per person per day by the primary trip mode among the days with more than 16 hours of Daynamica app data

Primary Mode	Number of Trips per Person per Day (%)			Travel Duration in Minutes per Person per Day (%)			Travel Distance in Miles per Person per Day (%)		
	Weekday	Weekend	All Trips	Weekday	Weekend	All Trips	Weekday	Weekend	All Trips
Bike	0.05 (1.0)	0.54 (11.1)	0.05 (1.0)	0.98 (1.0)	0.92 (0.9)	0.96 (1.0)	0.19 (0.5)	0.19 (0.4)	0.19 (0.5)
Bus	0.04 (0.8)	0.02 (0.4)	0.03 (0.8)	1.03 (1.1)	0.26 (0.3)	0.85 (0.9)	0.23 (0.6)	0.14 (0.3)	0.21 (0.5)
Car	3.71 (74.6)	4.29 (87.9)	3.84 (77.6)	87.13 (88.9)	90.21 (92.3)	87.8 (89.6)	36.35 (97.5)	45.46 (98.3)	38.4 (97.6)
Other	0.02 (0.4)	0.04 (0.8)	0.03 (0.6)	1.25 (1.3)	0.91 (0.9)	1.17 (1.2)	0.06 (0.2)	0.22 (0.5)	0.10 (0.3)
Rail	0.01 (0.2)	0.003 (0.1)	0.01 (0.2)	0.32 (0.3)	0.08 (0.1)	0.26 (0.3)	0.06 (0.2)	0.02 (0.0)	0.05 (0.1)
Walk	1.13 (22.7)	0.47 (9.6)	0.98 (19.8)	7.35 (7.5)	5.4 (5.5)	6.91 (7.1)	0.42 (0.01)	0.24 (0.5)	0.38 (1.0)
Total	4.97 (100)	4.88 (100)	4.94 (100)	98.05 (100)	97.77 (100)	97.99 (100)	37.30 (100)	46.26 (100)	39.34 (100)

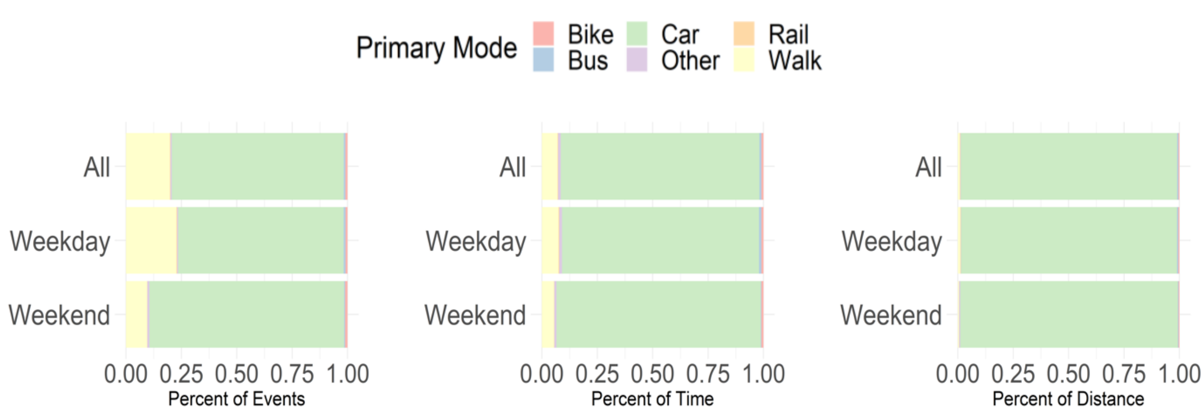


Figure 7: Percentage Breakdowns by Primary Mode of Trips, Time of travel, and Distance traveled

Table 5 indicates that for most participants, the trip purpose was heading to Work or Home. These destinations account for over 50% of the trip purposes for weekdays. Traveling to Work dropped dramatically during the weekend, from 1.61 trips per weekday to 0.09 trips per weekend. Shopping and Leisure & Recreation increased by about 0.5 events per day on weekends compared to weekdays. The pattern continues when examining minutes and miles per day.

The average minutes per trip or miles per trip stratified by trip purpose can be calculated by dividing elements of the 2nd or 3rd column by the 1st column. Common denominators were used for Weekday, Weekend, and All Trips columns within each section and will cancel out, resulting in proper units of Minutes per Trip or Miles per Trip. For example, while only 0.32 miles were traveled per person per day for education trips, the actual distance on average per education trip is actually 0.32 ÷ 0.05 or 6.4 miles per trip.

Table 5: Average trip frequency, duration, and distance per person per day by trip purpose among the days with more than 16 hours of Daynamica app data

Trip Purpose	Number of Trips per Person per Day (%)			Travel Duration in Minutes per Person per Day (%)			Travel Distance in Miles per Person per Day (%)		
	Weekday	Weekend	All Trips	Weekday	Weekend	All Trips	Weekday	Weekend	All Trips
Home	1.31 (26.4)	1.57 (32.1)	1.37 (27.7)	29.45 (30.0)	35.45 (36.3)	30.82 (31.5)	10.51 (28.2)	14.68 (31.8)	11.46 (29.1)
Work	1.61 (32.4)	0.09 (1.8)	1.27 (25.7)	28.31 (28.9)	3.64 (3.7)	22.70 (23.2)	10.61 (28.5)	0.83 (1.8)	8.38 (21.3)
Education	0.06 (1.2)	0.02 (0.4)	0.05 (1.0)	1.66 (1.7)	0.35 (0.4)	1.36 (1.4)	0.35 (0.9)	0.22 0.5)	0.32 (0.8)
Shop	0.38 (7.7)	0.92 (18.9)	0.51 (10.3)	6.67 (6.8)	13.24 (13.5)	8.16 (8.3)	2.88 (7.7)	7.00 (15.1)	3.82 (9.7)
Eat Out	0.27 (5.4)	0.42 (8.6)	0.31 (6.3)	4.66 (4.8)	7.52 (7.7)	5.31 (5.4)	1.90 (5.1)	3.45 (7.5)	2.25 (5.7)
Personal Business	0.55 (11.1)	0.51 (10.5)	0.54 (10.9)	11.02 (11.2)	12.53 (12.8)	11.36 (11.6)	4.30 (11.5)	5.5 (11.9)	4.58 (11.6)
Leisure & Recreation	0.32 (6.4)	0.88 (18.0)	0.45 (9.1)	5.97 (6.1)	15.58 (15.9)	8.16 (8.3)	2.90 (7.8)	8.59 (18.6)	4.20 (10.7)
Other	0.38 (7.7)	0.44 (9.0)	0.40 (8.1)	7.62 (7.8)	8.72 (8.9)	7.87 (8.0)	3.17 (8.5)	5.29 (11.4)	3.65 (9.3)
No Trip Purpose	0.07 (1.4)	0.03 (0.6)	0.06 (1.2)	2.69 (2.8)	0.74 (0.8)	2.25 (2.3)	0.68 (1.8)	0.6 (1.4)	0.67 (1.7)
Total	4.97 (100)	4.88 (100)	4.94 (100)	98.05 (100)	97.77 (100)	97.99 (100)	37.30 (100)	46.26 (100)	39.34 (100)

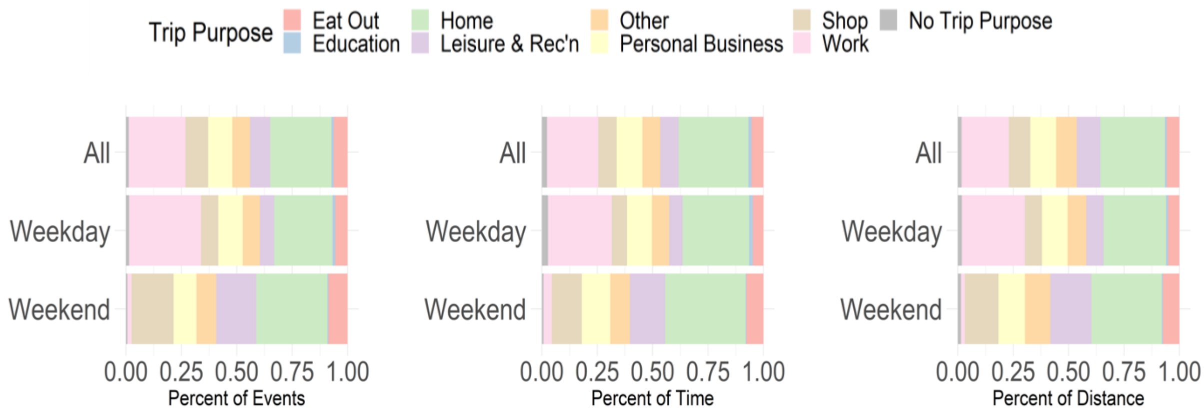


Figure 8: Percentage Breakdowns by Trip Purpose of Trips, Time of travel, and Distance traveled

4.3 SINGLE-MODE TRIP SEGMENTS

The 16,845 complete trips tabulated and discussed above were comprised of 22,349 separate mode segments. Table 6 details the number and characteristics of segments stratified by mode. Participants completed an average of 6.56 trip segments per day. This took on average 98 minutes to complete and the average distance traveled was 39.34 miles. The total number of miles traveled by the entire study totaled to approximately 130,556 miles with 97.4 percent of traveled by Car. The environmental impact of these car trips from 3,407 person days of traveling by car is around 118,000 pounds or 53.5 metric tons of CO_2 emitted from burning slightly under 6000 gallons of gas (EPA 2018). The average number of vehicle miles traveled per day varied between weekdays and weekends with 36.23 or 45.4 miles per day being traveled respectively.

Table 6: Average trip segment frequency, duration, and distance per person per day by the segment mode among the days with more than 16 hours of Daynamica app data

Segment Mode	Number of Trip Segments per Person per Day (%)			Travel Duration in Minutes per Person per Day (%)			Travel Distance in Miles per Person per Day (%)		
	Weekday	Weekend	All	Weekday	Weekend	All	Weekday	Weekend	All
Bike	0.08 (1.2)	0.09 (1.5)	0.08 (1.2)	1.00 (1.0)	1.02 (1.0)	1.01 (1.0)	0.19 (0.5)	0.2 (0.4)	0.19 (0.5)
Bus	0.05 (0.7)	0.02 (0.3)	0.04 (0.6)	0.79 (0.8)	0.25 (0.3)	0.67 (0.7)	0.20 (0.5)	0.14 (0.3)	0.19 (0.5)
Car	4.47 (67.0)	4.86 (78.5)	4.55 (69.4)	82.76 (84.4)	86.32 (88.3)	83.57 (85.3)	36.23 (97.1)	45.4 (98.1)	38.32 (97.4)
Other	0.05 (0.7)	0.06 (1.0)	0.05 (0.8)	1.74 (1.8)	1.68 (1.7)	1.73 (1.8)	0.07 (0.2)	0.22 (0.5)	0.1 (0.3)

Rail	0.02 (0.3)	0.01 (0.2)	0.02 (0.3)	0.33 (0.3)	0.11 (0.1)	0.28 (0.3)	0.07 (0.2)	0.02 (0.0)	0.06 (0.2)
Walk	2.00 (30.0)	1.16 (18.7)	1.81 (27.6)	11.43 (11.7)	8.4 (8.6)	10.74 (11.0)	0.54 (1.4)	0.29 (0.6)	0.48 (1.2)
Total	6.67 (100)	6.19 (100)	6.56 (100)	98.05 (100)	97.77 (100)	97.99 (100)	37.30 (100)	46.26 (100)	39.34 (100)

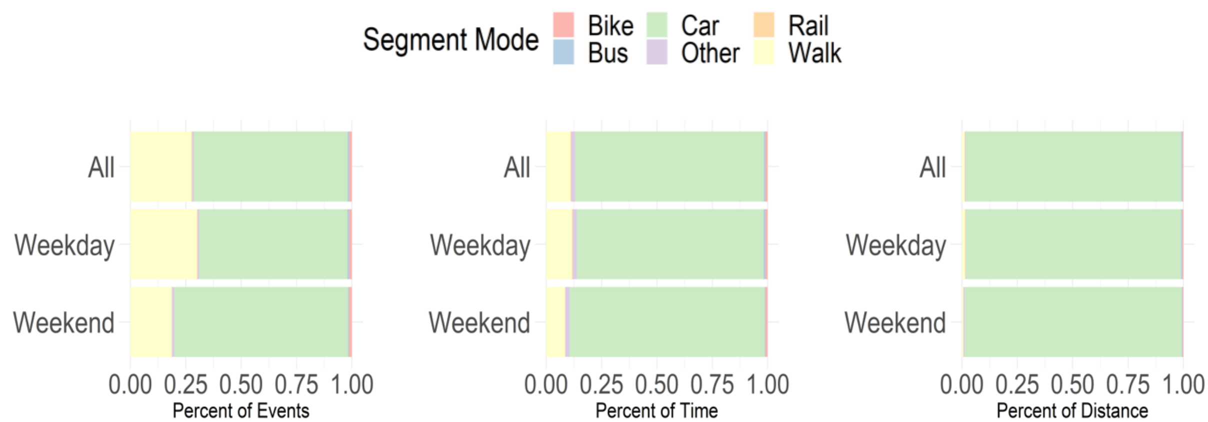


Figure 9: Percentage Breakdowns by Segment Mode of Trips, Time of travel, and Distance traveled

4.4 TRIP ORIGIN-DESTINATION PAIRS

Figures 10, 11, and 12 show hotspots in the counts, distance, and duration of trips stratified by the origin and destination activity of the trips. Dark purple corresponds with higher values, while dark green corresponds with lower values. Cells that contain white with intersecting gridlines represent origin and destination pairings that were not observed. The grids are also stratified based on all days, weekdays, or weekends. Note that these grids are not symmetric since the frequency of trips going from Home to Shopping may not be equal to trips going from Shopping to Home.

Hot spots occur during Home to Work and Work to Home trips for weekdays, but this does not happen for weekends. Instead on weekends, we see new hotspots for Home to Shop and Shop to Home. These patterns are more pronounced in Figure 11 (distance traveled) and Figure 12 (time spent). This indicates that participants usually drove further to and from Work but preferred Shopping at locations closer to their Home.

Figure 10: Number of trips per week by Origin-Destination Activity Pairs

Figure 11: Distance traveled (miles) per week by Origin-Destination Activity Pairs

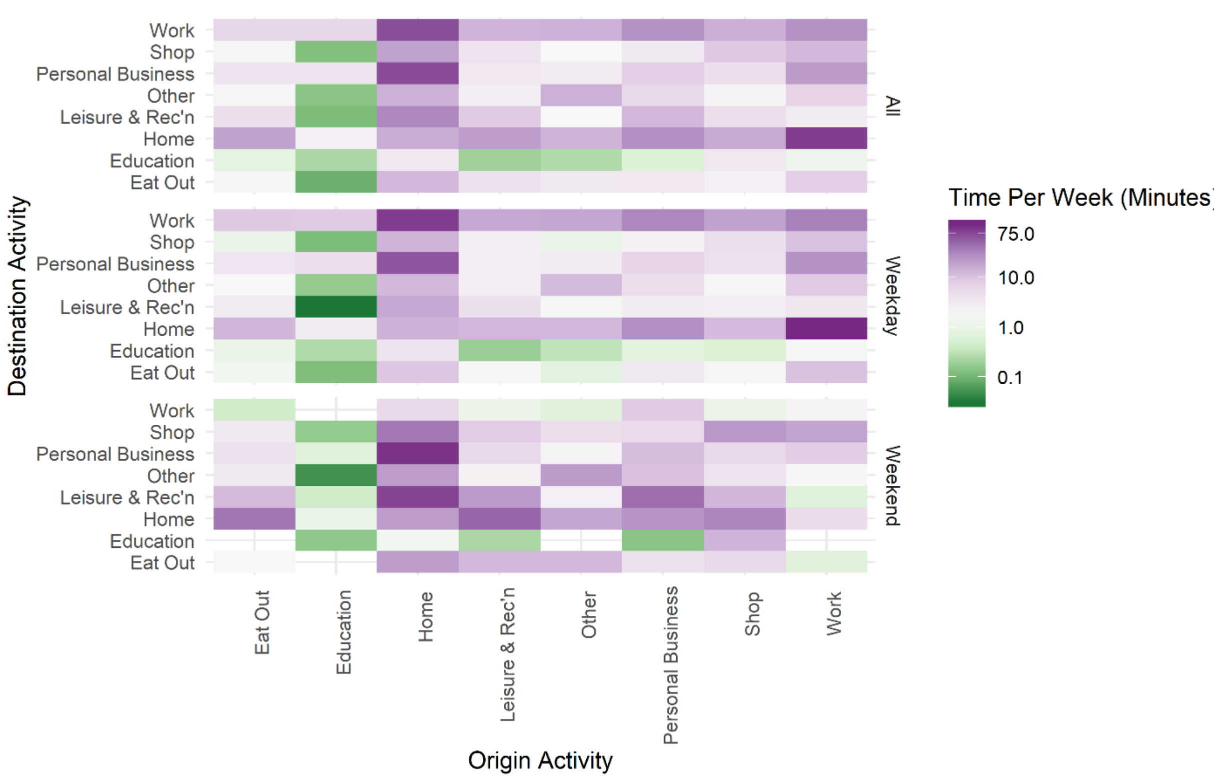


Figure 12: Time (minutes) traveled per week by Origin-Destination Activity Pairs

CHAPTER 5: PARTICIPANT REACTIONS TO ALTERNATIVE MODE RECOMMENDATIONS FOR CAR TRIPS

In the Phase 2 Intervention, the app was modified to include a two-question survey that asked participants to rate whether each alternative mode recommendation they received was reasonable, and whether they would ever consider trying that recommendation. The survey feature was only accessible for participants in the Phase 2 Intervention group who viewed at least one of the travel recommendations. Surveys could not be filled out if no recommendations were viewed, and participants could choose to view recommendations for only a subset of all possible recommended modes. Recommendations and the associated surveys were only provided for completed car (as the primary mode) trips. Participants in Phase 2 had the ability to update a previously filled out survey and change the response. Figure 5 in Chapter 2 shows the format and wording of the in-app survey.

Over the course the Phase 2 Intervention, 1,309 surveys were filled out by 37 participants, approximately 35 survey per participant. The surveys were conducted at the trip level so each participant completed multiple surveys. Analyses were performed to assess the probabilities of whether a participant would considered a particular alternative mode recommendation reasonable (question 1) or wroth trying (question 2). When a mode recommendation is selected for either question, the alternative travel mode recommendation was considered successful. The context for the success is described by whether the recommendation is considered reasonable and whether the participant would ever consider trying the recommendation.

This chapter is broken into two distinct sections, one to focus on descriptive statistics for the surveys taken, and the other will focus on modeling the probability of selecting a mode in the survey.

5.1 DESCRIPTIVE ANALYSES

As shown in Table 7, 1,309 surveys were completed. Of those, 368 were considered commute trips in which the origin-destination pair were either Home-Work or Work-Home respectively. The remainder of the surveys, 908, were for non-commute trips. Overall, 46.5 percent of survey responses considered one of the recommendations reasonable (question 1), with a higher percentage of commute trips considered reasonable compared to non-commute trips (55.7% vs 42.8%). The transit and biking recommendations were considered the most reasonable. The Park & Ride recommendations had the highest relative difference in reasonableness between commute and non-commute trips (16.0% vs 5.8%). There is also a significant increase in reasonableness when considering walking recommendations on non-commute trips compared to commute trips. These patterns are also evident when examining whether participants would consider trying the recommendations provided (question 2), but with lower overall success rates of the recommendations.

Table 7: Brief Survey Results

	All Trips (%)	Commute Trips; Home-to-Work and Work-to-Home (%)	Non-Commute Trips (%)
# surveys	1,309	368	908
# any reasonable	609 (46.5%)	205 (55.7%)	389 (42.8%)
Transit reasonable	331 (25.3%)	129 (35.1%)	192 (21.1%)
Park & Ride reasonable	117 (8.9%)	59 (16.0%)	53 (5.8%)
Biking reasonable	217 (16.6%)	54 (14.7%)	161 (17.7%)
Walking reasonable	90 (6.9%)	7 (1.9%)	83 (9.1%)
# consider trying	470 (35.9%)	162 (44.0%)	296 (32.6%)
Transit consider trying	253 (19.3%)	104 (28.3%)	142 (15.6%)
Park & Ride consider trying	84 (6.4%)	43 (11.7%)	34 (3.7%)
Biking consider trying	149 (11.4%)	37 (10.1%)	111 (12.2%)
Walking consider trying	60 (4.6%)	4 (1.1%)	56 (6.2%)

The trip-level surveys also provide the opportunity to look at intra-person variations. Figure 13 looks at the proportion of car trips of which any alternative mode recommendation was considered reasonable and the corresponding confidence intervals for each participant in the Phase 2 Intervention group from ID 1 to ID 37. There are three sub-plots from left to right in Figure 13. The left sub-plot looks at surveys related to all car trips, the middle sub-plot looks at surveys related to commute trips—defined as car trips between Home and Work (both directions), and the right sub-plot looks at how commute trips compare to non-commute trips.

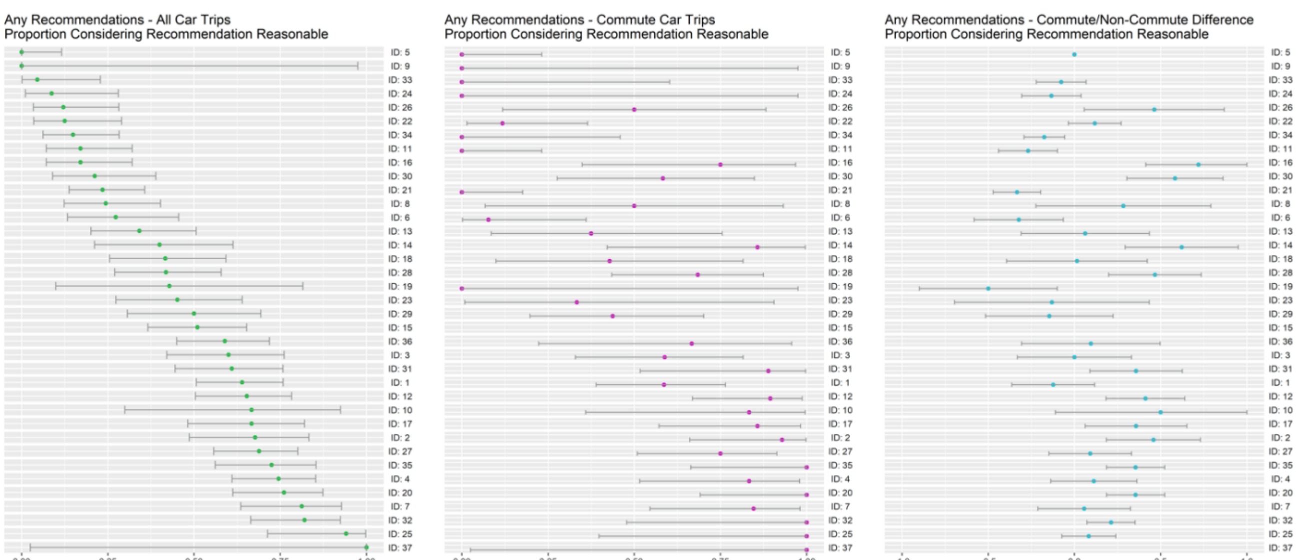


Figure 13: Intra-person variation in survey results—any recommendation being reasonable

As shown in the left sub-plot in Figure 13, there is substantial heterogeneity across participants in the proportion of recommendations that are considered reasonable. The proportions span between 0 and 1 with slightly more than half of the participants having overall proportions below 0.5. The middle sub-plot indicates that the majority of the people thought that the commute trip recommendations were reasonable at least 50 percent of the time, while the right sub-plot indicates that commute trips were considered reasonable more often than non-commute trips.

The explanations of Figure 13 above are equally applicable to Figure 14 below with minor modifications in interpretation. Figure 14 looks at the proportion of car trips of which transit mode recommendations in particular were considered reasonable and the corresponding confidence intervals for each participant. When looking at participant responses to transit recommendations, we see larger clusters around the extremes of 0 and 1 rather than the middle, unlike the more even spread illustrated in Figure 13. This indicates that most participants thought that all or none of the transit recommendations were reasonable while only few thought that some of the recommendations were reasonable and some were not. When it comes to comparing transit recommendations between commute and non-commute trips, Figures 13 and 14 have similar patterns: there is a higher percentage of transit recommendations for commute trips considered reasonable than those for non-commute trips.

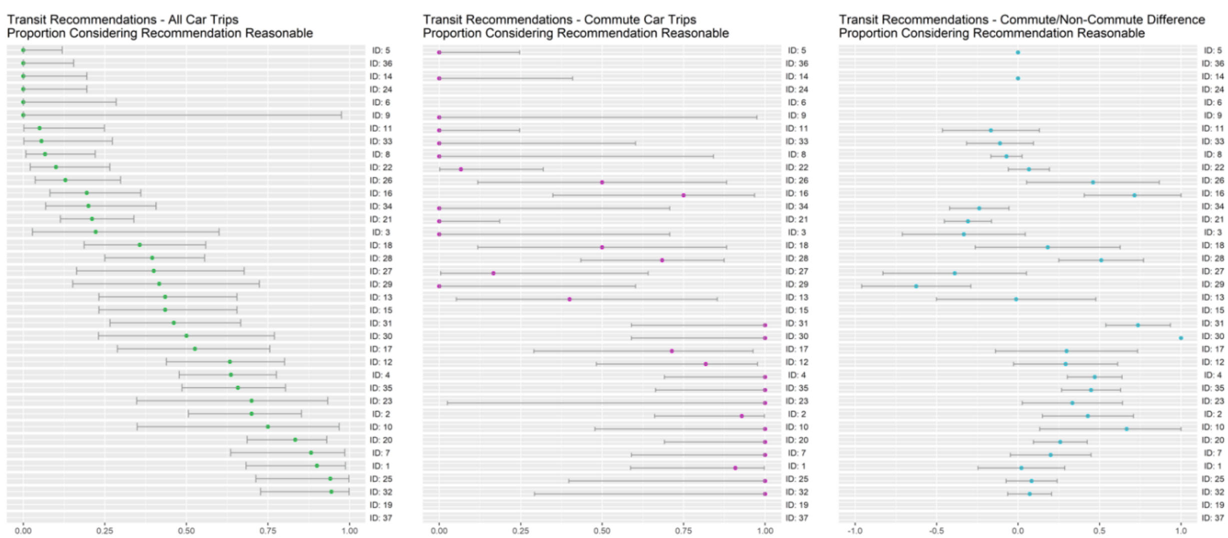


Figure 14: Intra-person variation in survey results—transit recommendation being reasonable

Figure 15 shows intra-person variations when it comes to the Park & Ride recommendations, illustrating significant deviations from the patterns shown in Figures 13 and 14 above. Almost half of participants thought that none of the Park & Ride recommendations were reasonable. In the right sub-plot in Figure 15 below, a large portion of the point estimates are centered at 0. This indicates that there was no difference in Park & Ride recommendations between commute and non-commute trips; however, this is because the participants did not consider any of the recommendations reasonable.

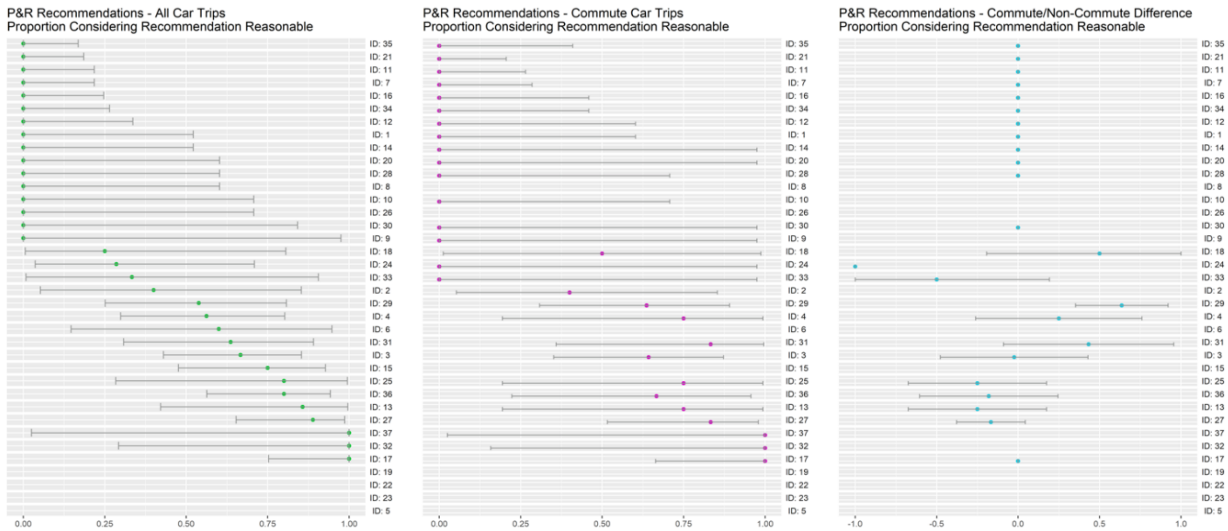


Figure 15: Intra-person variation in survey results—Park & Ride recommendation being reasonable

Figures 16–18 correspond with question 2 in the survey, whether a participant would ever consider trying the recommendation provided. The left sub-plot of Figure 16 illustrates a diverse set of opinions on the recommendations. In this case, when considering trying the recommendation, the set of proportions is shifted slightly lower than when considering whether the recommendations were reasonable. Around two thirds of the participants had a proportion lower than 0.5. The middle sub-plot only a slightly follows the increasing trend from low to high proportion as we go down the plot as shown in the left sub-plot; indicating that commute trips may not be the driving factor in successful response rates. However, the right sub-plot shows that participants are more likely to consider trying recommendations for commute trips than non-commute trips. Participants who would consider trying a higher proportion of trips were also more likely to consider commute trips than non-commute trips.

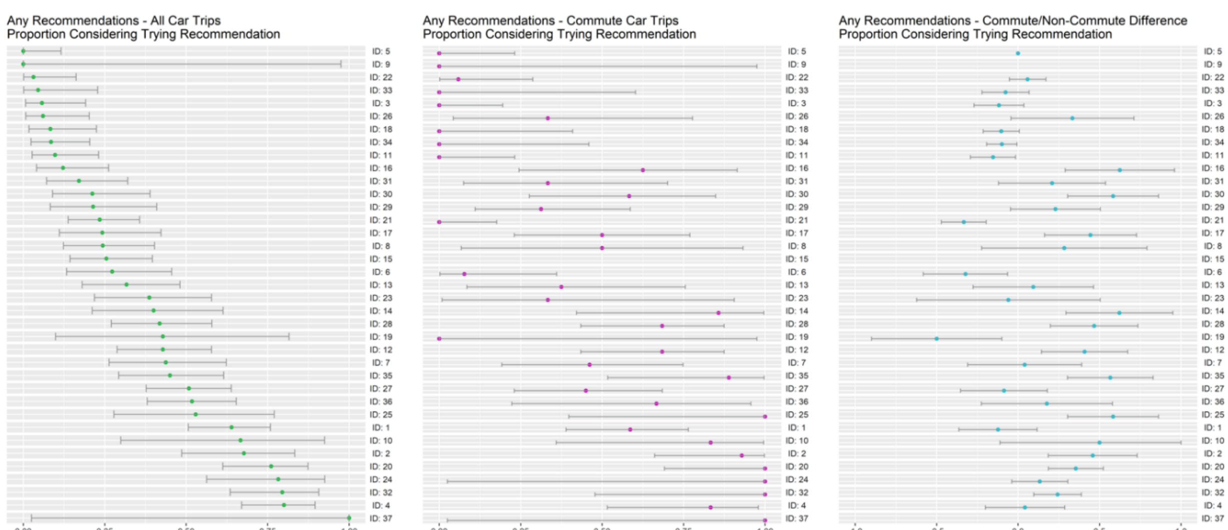


Figure 16: Intra-person variation in survey results—consider trying any recommendation

Only minor differences occurred in Figure 17 (whether they would consider trying the transit recommendations only), compared to Figure 16. One difference was a higher overall number of participants indicating they would not consider trying transit recommendations for their car trips compared to those who consider trying any recommendations in Figure 16. Besides this, the general pattern of the data is quite similar to that of Figure 16.

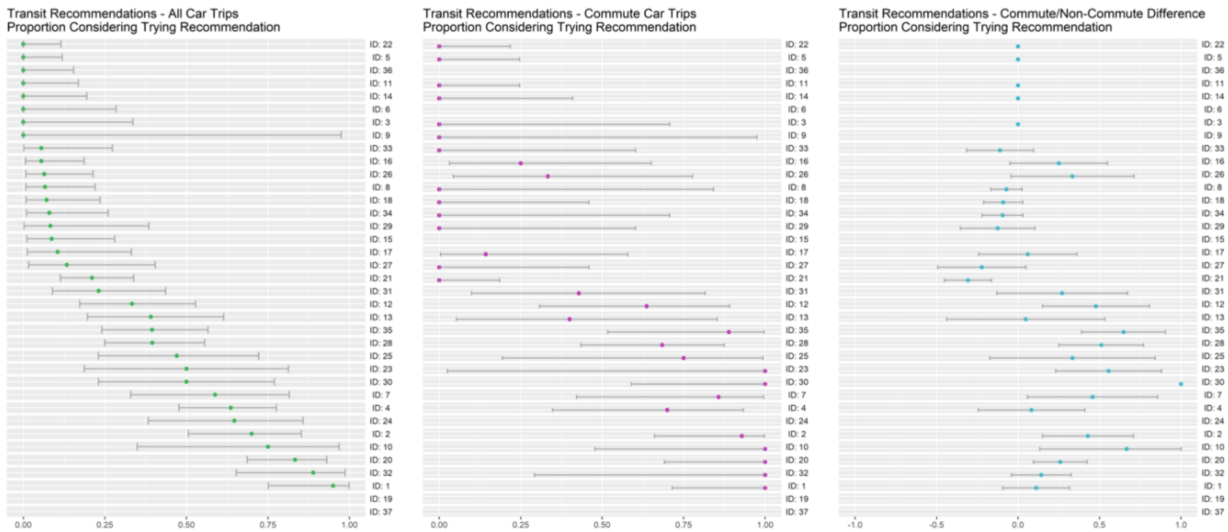


Figure 17: Intra-person variation in survey results—consider trying transit recommendation

In Figure 18 (whether they would consider trying the Park & Ride recommendations only), there is again a high proportion of participants who would not consider trying any of the Park & Ride recommendations provided, mirroring the response to question 1. Only eight participants stated at least 50 percent of the time that they would consider trying the Park & Ride recommendations. For commute only trips, there were nine participants who stated they would consider trying the recommendations provided more than half the time.

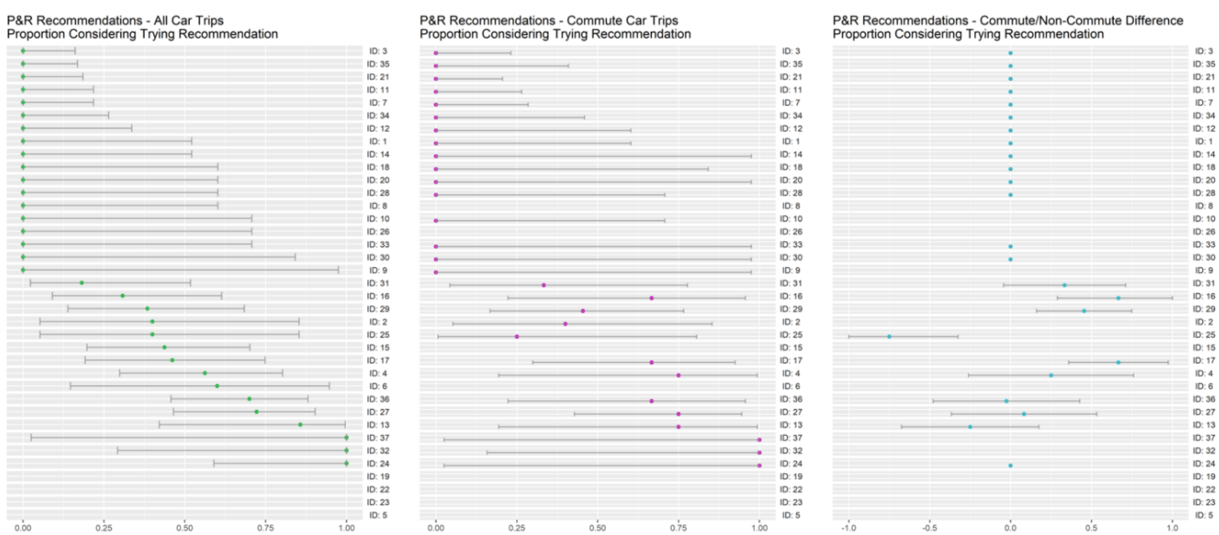


Figure 18: Intra-person variation in survey results—consider trying Park & Ride recommendation

5.2 REGRESSION ANALYSES

In addition to creating visualizations to show the proportion and confidence interval estimates for each participant in the Phase 2 Intervention, this report investigates how different attributes of the participants and the actual trips may affect the likelihood of selecting a box in a survey. Logistic regression models were implemented in order to estimate these effects. A mixture of characteristics associated with the participants as well as characteristics specific to individual trips were evaluated for inclusion in the model. Using stepwise variable selection, the final set of variables included in the model was:

- Indicator for whether the trip began before 7AM
- Indicator for whether the participant owns their own housing
- Indicator for whether the participant is a Male
- Indicator for whether the participant stops frequently on trips
- Indicator for whether the participant is interested in good options for public transportation
- Indicator for whether the participant stated that owning a car is no burden at all
- Indicator for whether the participant stated that owning a car is something of a burden
- Time difference between the actual Car trip and the Transit recommendation

The results of the models are presented in Figures 19–20. In each scenario, the models utilized the same set of variables. In certain instances, the parameter estimates or the corresponding confidence intervals were extremely small or large on the odds scale (< 0.004, > 256). For graphing purposes, these extreme values were censored at either 0.004 or 256 to construct the figures on identical scales. Variables that have been censored are indicated by grey dots instead of the standard maroon dots in the figures.

Below is a set of figures related to the logistic regression models. For interpreting the logistic regression model, do not focus on specific numeric values, but rather the general trends the figures illustrate. Interpret the figures by identifying which side of the dashed line and how far from the dashed line the estimate (effect) is. The vertical dashed line at 1 indicates that the parameter has no effect. If the dashed line is contained within the confidence interval, then the effect is not considered statistically significant at the 5 percent level. Discussion of results will be arranged in order of model variables.

The variable of leaving before 7AM appears to have a marginal positive impact on increasing the odds of a success occurring. The effect is most pronounced for Transit Recommendations, with statistically insignificant effects for the Park & Ride Recommendations. The Any Recommendation plots indicate that the effect of leaving before 7AM is on the edge of being considered statistically significant.

Owning your own housing is negatively associated with a success occurring. For this variable, statistical significance occurs for two scenarios, excluding Transit Recommendations. The effects are largest for the Any Recommendation scenarios. The effect of being a male lowers the odds of a success occurring; the effect is strongest for question 2 (whether they would consider trying a recommendation). The effect is not statistically significant for question 1 but is for the second question in all scenarios.

Frequent stopping during commute trips is negatively associated with a success occurring as well. For this variable, the effects are most pronounced for question 2, specifically in the Any Recommendation and Park & Ride Recommendation scenarios. This variable has the largest effect of the variable set in the figures shown below.

Interest in good options has a negative effect on the odds of success occurring. This effect is largest for Park & Ride Recommendation in question 2: whether the participant would consider trying a recommendation. Car burden is a 3-level factor. The baseline for the model is the car being a large burden. In comparison to owning a car being a large burden, thinking that the car is no burden at all is positively associated with successes, but this effect is insignificant except for the Park & Ride Recommendation scenario in question 2 (left panel of Figure 20). For those who considered owning a car to be something of a burden, differential behavior exists for the parameter estimates across each scenario. For Any or Park & Ride Recommendations, this variable has a negative association with success. For the Transit Recommendation, this association is positive. This is the only time in which the direction of effect for a parameter switched signs across scenarios.

The final parameter of interest is the time the Car trip took compared to the counterfactual time the Transit Recommendation would have taken. In all scenarios, this parameter was estimated at or close enough to be considered 0 and the confidence interval was extremely small. It appears that the time difference did not have a meaningful impact on the odds of a recommendation being a success.

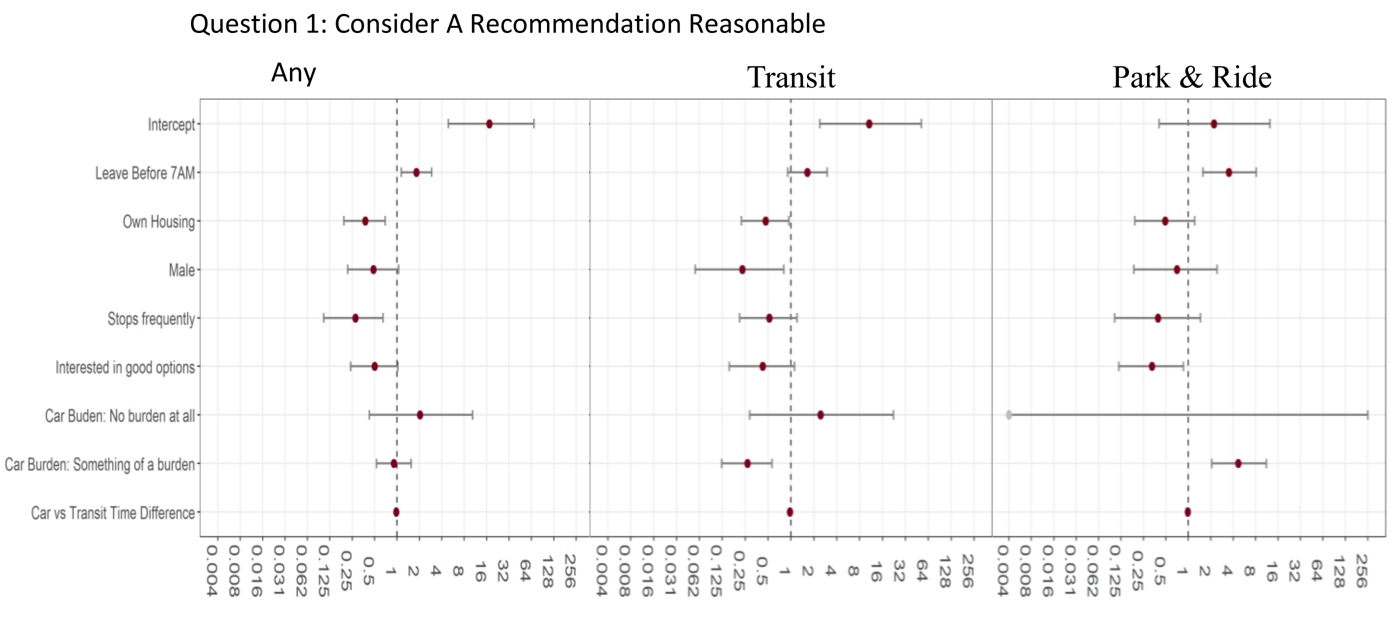


Figure 19: Odds ratio plot for considering a recommendation reasonable

Question 2: Consider Trying A Recommendation

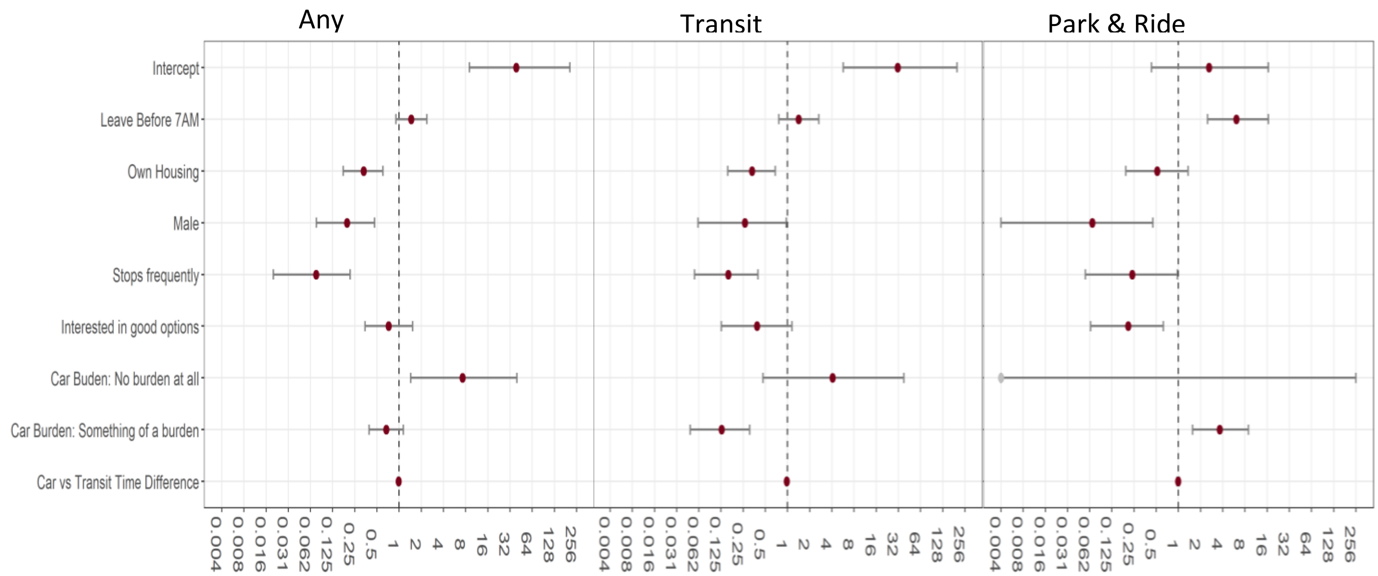


Figure 20: Odds ratio plot for considering trying a recommendation

CHAPTER 6: COMPARATIVE ANALYSIS OF THE ACTUAL AND RECOMMENDED TRAVEL BEHAVIOR

The Daynamica app was designed to produce travel recommendations for completed trips made by car. The primary focus of this analysis is to characterize the difference between the total trip time of the actual Car trips and the total trip time of the recommendation, especially the two transit-involved modes (i.e., Park and Ride; and Transit). The analysis in this chapter includes recommendations generated during the Phase 2 intervention which have associated surveys discussed in Chapter 5. Car trip data only includes trips for which recommendations were present; the set of viable Car trips for Park and Ride recommendations is not the same as the set of viable Car trips for Transit recommendations; some car trips did not have both alternative modes available.

Table 8 contains the basic summary statistics of a comparison between the transit-involved recommendations produced and the values observed by the Car trips. On average, the recommendations have a longer travel time than driving a car. The Park and ride recommendations have an average 50-minute travel time while same set of trips made by Car have an average 30-minute travel time. The Transit recommendations have an average 30-minute travel time while the same set of trips made by car have an average 20-minute travel time.

Table 8: Descriptive Statistics of Counterfactuals

Trip Category		**Actual Car Trip Time**	**Recommendation Time**
139 Trips with P&R suggestions	Mean (SD)	31.7 (61.1)	50 (29)
	Median (IQR)	19.5 (11.2, 29.5)	46 (34.5, 57.5)
317 trips with transit suggestions	Mean (SD)	19 (38.7)	28.5 (26)
	Median (IQR)	10.5 (3.5, 23)	24 (2, 42)

Plots, in Figures 21–23, have also been constructed to display the relationship between the time difference of the recommended versus actual trip and the associated survey responses. The Y-Axis displays the travel time of the recommendation and the X-Axis shows the travel time of the actual trip. Color of the point indicates whether the participant thought that specific recommendation was reasonable, and shape of the point indicates whether the participant would consider trying the recommendation; for example, a blue triangle indicates the participant thought that the recommendation was reasonable and would consider trying the recommendation. A diagonal black line is plotted at a 45-degree line on the linear scale to help identify whether the recommendation travel time is shorter or longer than the actual value.

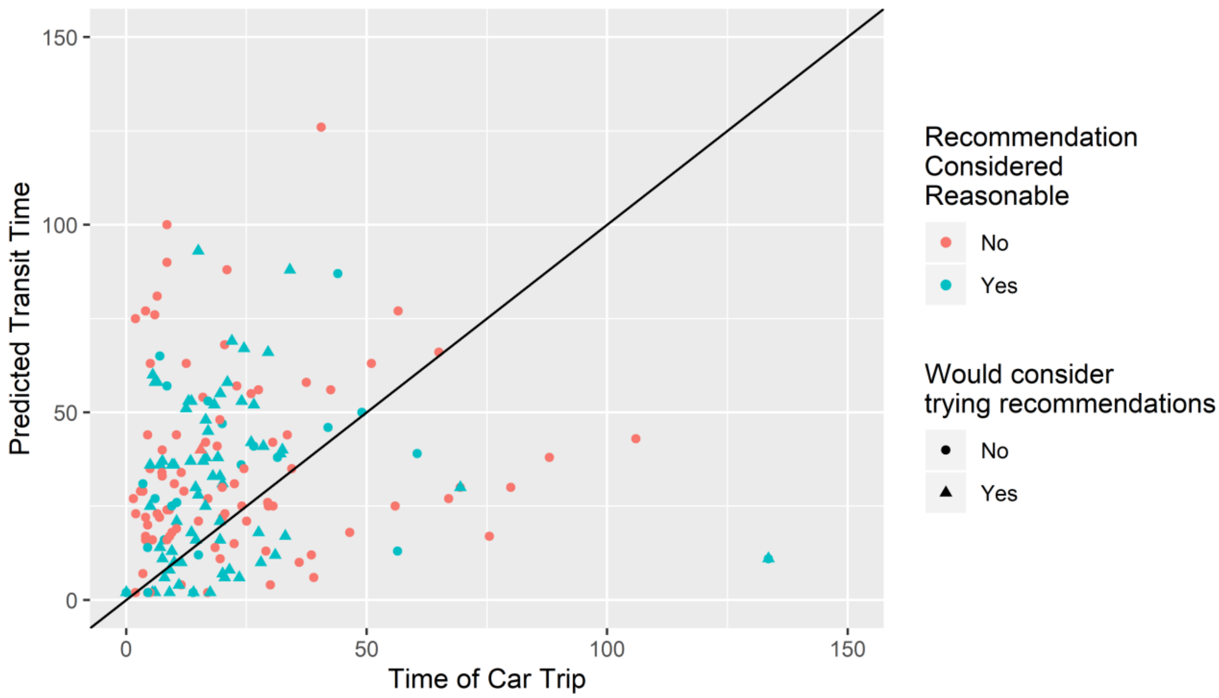


Figure 21: Transit Counterfactual Recommendations Comparisons

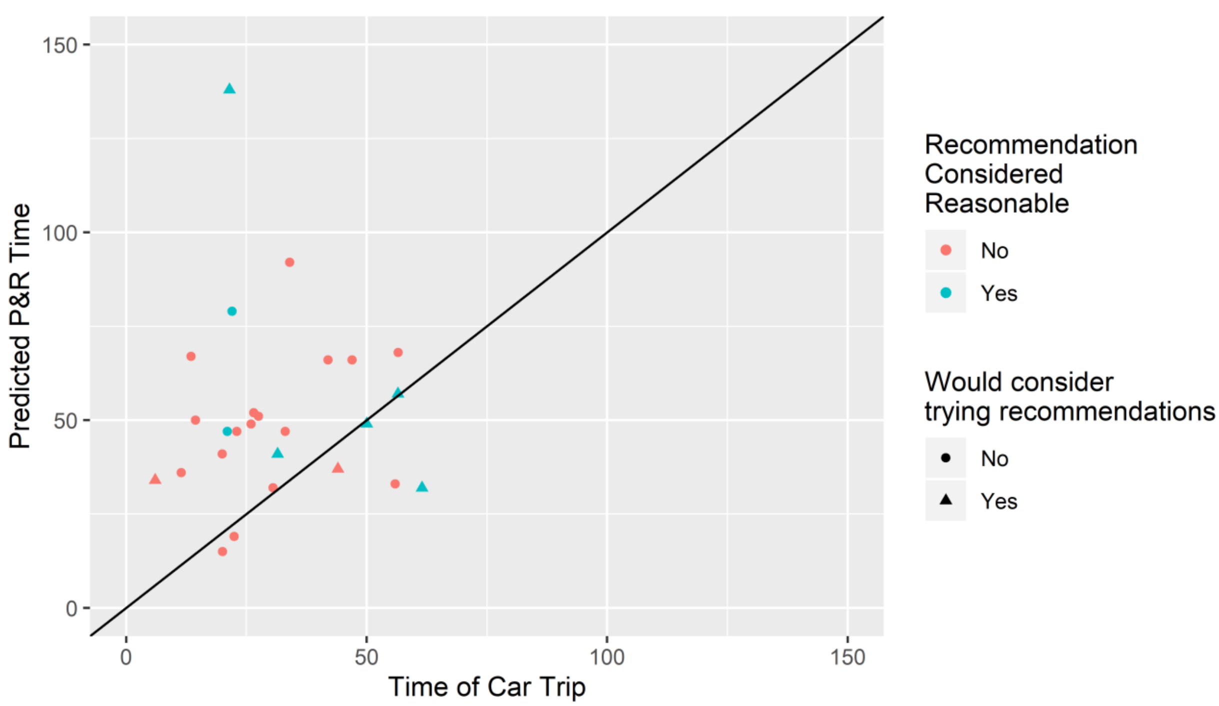


Figure 22: Park & Ride Counterfactual Comparison Plot

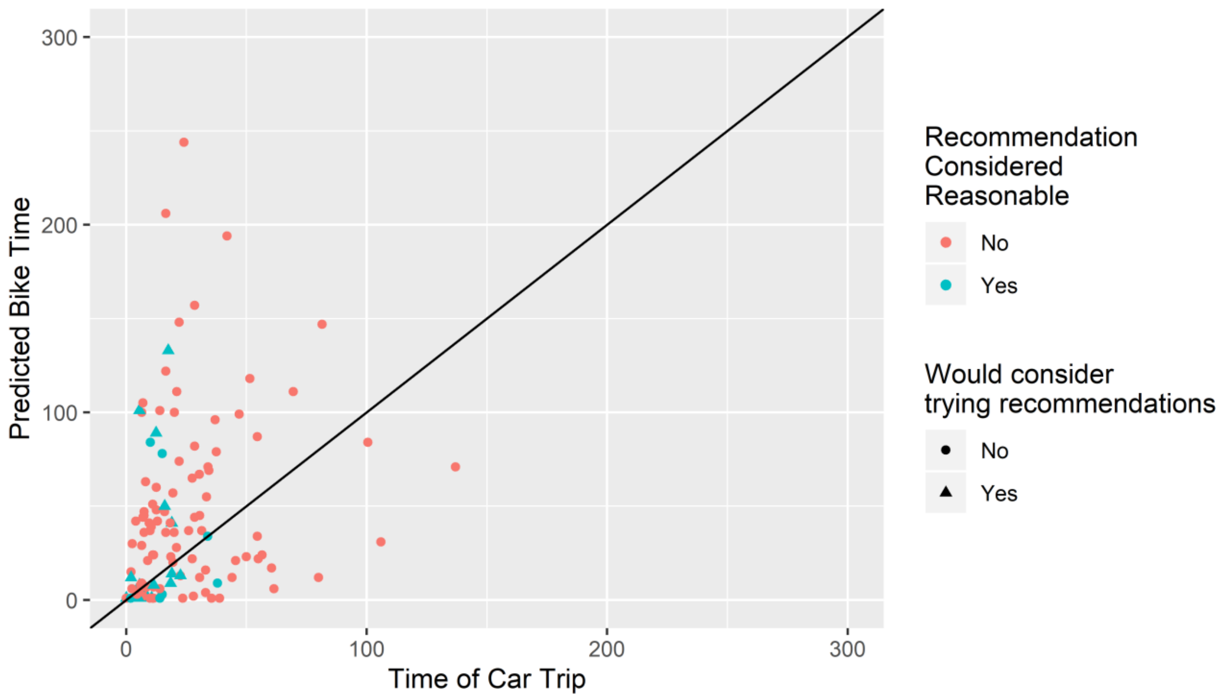


Figure 23: Bike Counterfactual Comparison Plots

The majority of the data points fall above the black line indicating that the recommendations take longer than car trips. In addition to this, the proportion of red to blue is higher above the line than below the line indicating that recommendations that take less time than actual trips are likely to be considered reasonable travel recommendations.

Future analyses can explore modified algorithms for generating recommendations. Numerous choices were made when developing the methods for presenting alternative travel mode recommendations. These choices could be modified to evaluate the impact if participants followed through on this new regime of alternative travel recommendations. It would not be possible to ascertain the reasonableness of these new recommendations though, as the reasonableness was linked to the surveys that the users completed while participating in the study.

CHAPTER 7: ACTIVITY CHAINING ANALYSIS

With the Daynamica smartphone application, we can observe the daily activity patterns of study participants and analyze differences; however, effectively characterizing the activity patterns of participants in a large study is a difficult task. The sheer volume of information can be insurmountable, with thousands of days of information collected. Data must be summarized and collated to account for the magnitude of data collected throughout a study.

Activity chaining is a novel method for summarizing activity-trip data to visualize participant behavior. We followed these steps to create the Activity Chains:

- Activity-trip data was grouped by participant on a per day basis
- All trip data was removed
- All activities less than 30 minutes were removed
- The activity data was simplified to only contain the activity type
- The Leisure and Recreation, Eat Out, Personal Business, Shop, and Other activity types were combined into a single Out-and-About (O) category
- The Work and Education activity types were combined into a Sustenance (S) category
- Home activities were kept alone in a Home (H) category
- After recategorizing, duplicate categories that are adjacent in the activity chain (e.g., HHSSOH has H and S duplicates) were merged to remove the duplication (e.g., HSOH has merged the duplicates). Duplicates arise from the removed trips and short activities.
- An X label is added at the end of each individual chain to indicate that the chain has ended for the day.

These steps are not the only method to produce activity chains. Chains may also include a label to indicate when information is missing. This analysis was exploratory in nature. Any other number of modifications may be made to the construction of chains depending on the interest of the researcher.

This study tabulates the activity chain data in two ways: by counting the number of chains that have an identical match to a reference chain (the absolute method); and by tracking the sequencing of similar activity chains, for example, the number of chains that start with H, the number of chains that proceed to O, etc. (the cumulative method).

Table 9 details the absolute activity chain tabulation and Table 10 details the cumulative activity chain tabulation. The tables show only those chains with a frequency of more than 1%.

Table 9: Absolute Activity Chain Tabulation with 1% Pruning; Percentages are based on the chains included in the analysis (after pruning), not all chain combinations.

Chain	Count	Percentage
HSOH	424	15.6
HSH	349	12.8
HOH	344	12.7
HOSOH	252	9.3
HOHOH	225	8.3
HSHOH	136	5
HOSH	130	4.8
HSOSOH	99	3.6
O	87	3.2
HOHOHOH	80	2.9
HSOHOH	65	2.4
OSO	58	2.1
H	57	2.1
HSOSH	57	2.1
OH	55	2
HOSOSOH	53	1.9
HOSOHOH	51	1.9
HO	50	1.8
HSO	43	1.6
HOSO	36	1.3
HOSHOH	34	1.3
HS	34	1.3
Total*	2719	100%

Note: The chains listed above are included because they had at least 34 user-days of data (1% of all user-days). Percentages are based on the tabulated dataset, not of possible chains.

We see that the most popular chain performed by participants is HSOH. 424 days were spent by participants leaving Home, going to Work, then Out-and-About, then back Home to end the day. HSH and HOH were also common activity chains, these occurred 349 and 344 times. HOSOH and HOHOH happened 252 and 225 times respectively. These could reasonably be classified as diversions from the regular schedule of HSH either on their way from or to Home. Another important chain to highlight is HSHOH which would be considered instances of going out again after Work. This happened 136 times.

Table 10 has information on the sequencing of activity categories. The previous string column indicates what the previous character(s) in the activity chain and the current string column indicates the next character of the chain. Because of this structure, the table is ordered alphabetically instead of by counts. The absolute count is the number of chains that started with the previous string and had the following category in the current string. The relative percentage indicates the percentage of the chains with that current string that have the same previous string sequence. For example, with a previous string of H, a relative percentage of 51 percent for the current string of O indicates that 51 percent of the strings that start with H started as HO. An X in the current string indicates that the previous string is the entire activity chain. Missing segments have been omitted from being displayed in this table. Because of missing segments and pruning, the relative percentages will normally not add up to 100 percent.

Table 10: Cumulative Activity Chain Tabulation with 1% pruning

Previous String	Current String	Absolute Count	Relative Percentage
	H	2964	87%
	O	330	10%
	S	103	3%
H	O	1498	51%
H	S	1409	48%
H	X	57	2%
HO	H	771	51%
HO	S	677	45%
HO	X	50	3%
HOH	O	383	50%
HOH	S	44	6%
HOH	X	344	45%
HOHO	H	340	89%
HOHOH	O	115	34%
HOHOH	X	225	66%
HOHOHO	H	108	94%
HOHOHOH	X	80	74%
HOS	H	182	27%
HOS	O	475	70%
HOSH	O	51	28%
HOSH	X	130	71%
HOSHO	H	43	84%
HOSHOH	X	34	79%
HOSO	H	325	68%
HOSO	S	114	24%
HOSO	X	36	8%
HOSOH	O	72	22%
HOSOH	X	252	78%
HOSOHO	H	59	82%
HOSOHOH	X	51	86%
HOSOS	O	81	71%
HOSOSO	H	65	80%
HOSOSOH	X	53	82%
HS	H	540	38%
HS	O	835	59%

Previous String	Current String	Absolute Count	Relative Percentage
HS	X	34	2%
HSH	O	171	32%
HSH	X	349	65%
HSHO	H	151	88%
HSHOH	X	136	90%
HSO	H	520	62%
HSO	S	272	33%
HSO	X	43	5%
HSOH	O	90	17%
HSOH	X	424	82%
HSOHO	H	71	79%
HSOHOH	X	65	92%
HSOS	H	101	37%
HSOS	O	161	59%
HSOSH	O	38	38%
HSOSH	X	57	56%
HSOSHO	H	35	92%
HSOSO	H	125	78%
HSOSOH	X	99	79%
O	H	106	32%
O	S	137	42%
O	X	87	26%
OH	O	41	39%
OH	X	55	52%
OS	O	104	76%
OSO	X	58	56%
S	H	35	34%
S	O	54	52%

Note: 10 user-days of data were not included in this table because the entire day consisted of travel or activities shorter than 15 minutes, meaning no activity chain could be constructed.

From Table 10, we notice that the vast majority of participants (2964 out of 3,497) started their day at Home. The majority of the participants, upon starting at home, went to Work (1409 chains starting with HS). In addition, 57 participant-days were spent at Home without ever leaving the Home. 38% of the time, after starting with HS, an H followed. 59% of chains that started with HS went to O.

The information presented in Tables 9 and 10 can also be represented in graphical format. The data in Table 10 is most analogous to the activity chaining plots presented below in Figure 24. The figures show how different activity chains diverge throughout the day. The colored bars represent the current string in the activity chain. The height of the bands connecting the flow of the activity chain is proportional to the relative percentage column in Table 10. It is important to note that pruning still occurs at 1%. This means that not all branches are included in the figure.

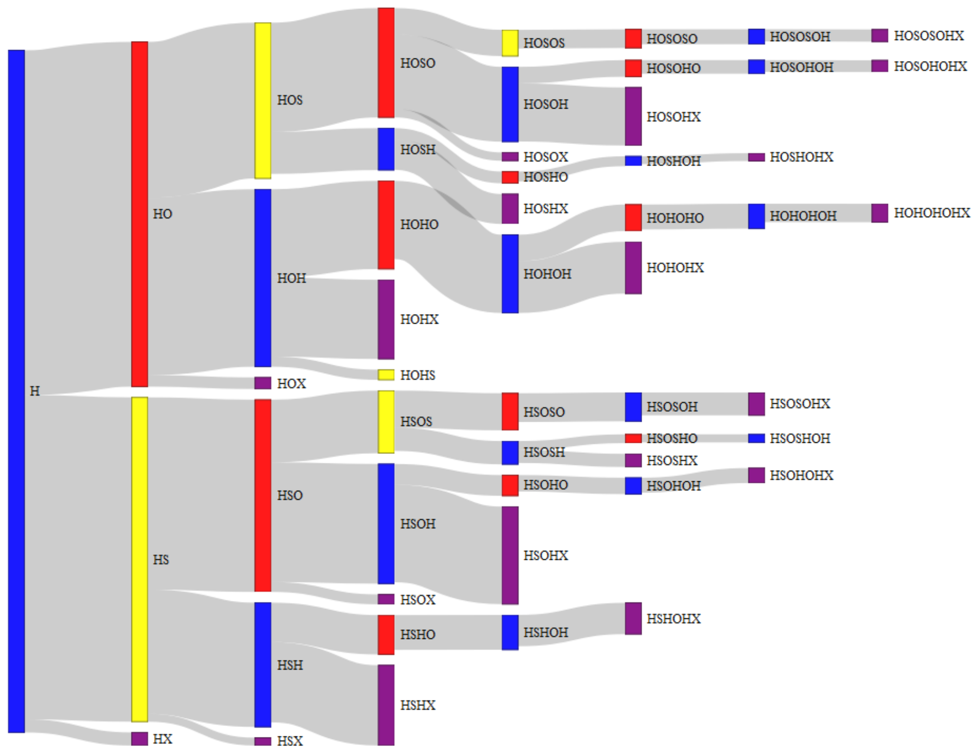


Figure 24: Activity Chaining Plot - All Data

Figure 24 only shows the activity chains in which Home is the starting activity to make the plot easier to view, interpret, and compare. Overall, from H, most chains proceed to S. This makes sense because the TOP study population consists of participants who work for the University of Minnesota and commute to campus. Following going to Work, HS, a large proportion of participants went Home, HSH, and following that, most did not leave the house again, HSHX. Some participants did end up going out after going to Work indicated by the chain HSO or HSHO.

Visual activity chain plots can be stratified by various participant characteristics to further investigate various daily activity patterns. Figure 25 shows the activity patterns for female participants (N=2,273 participant-days) and Figure 26 shows the patterns for male participants (N=681 participant-days). The male and female activity chains are mostly the same, with only one minor differences. There is a slightly higher proportion of female participants that are Out-and-About after the initial Home category, before moving to another activity.

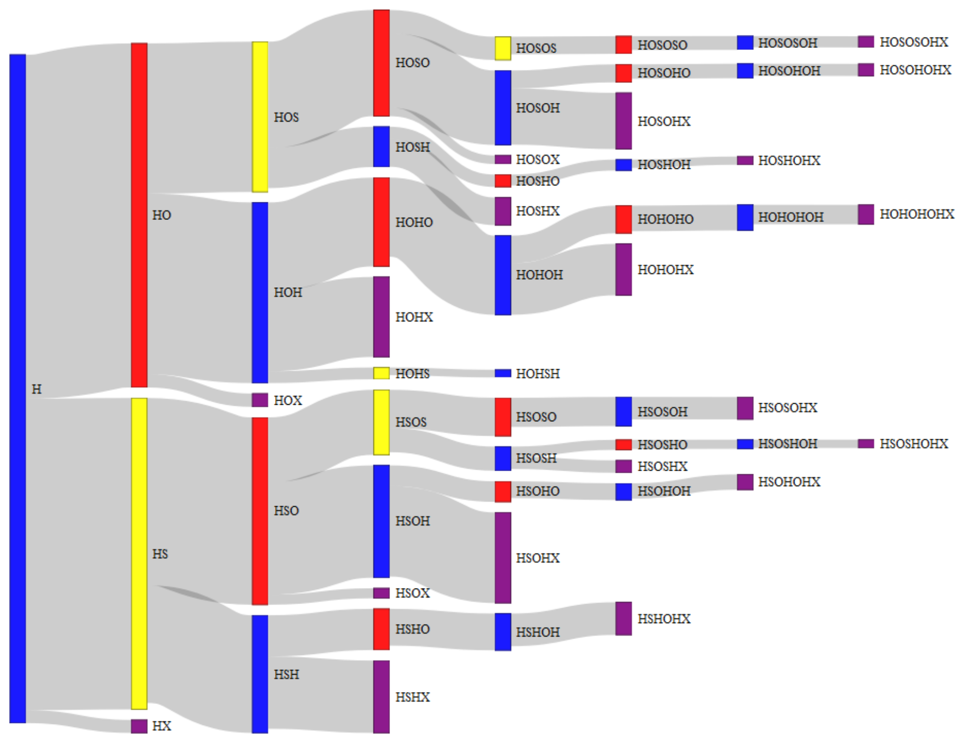


Figure 25: Activity Chaining Plot - Female Data

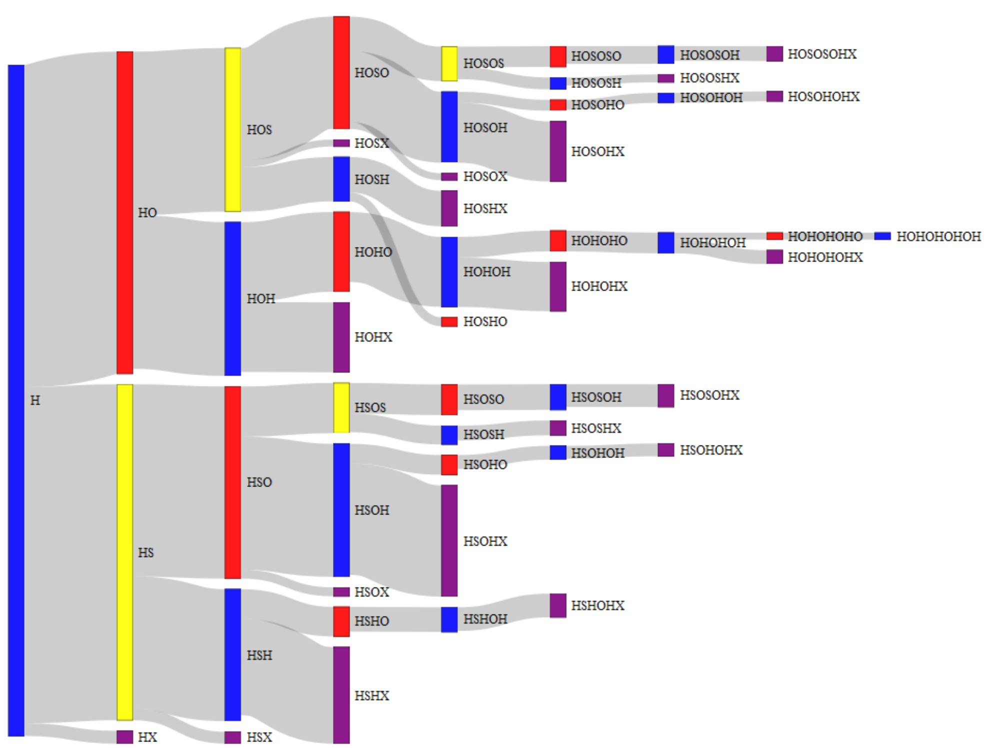


Figure 26: Activity Chaining Plot - Male Data

In contrast, there are dramatic differences between weekdays (Figure 27) and weekends (Figure 28). Expectedly, a significantly larger proportion of participants go from H to S in the weekday plot. In addition, the number of different branches or different types of chains in the plot is higher for the weekday indicating a greater diversity in activities. Weekend activity chains have a significantly lower proportion of Sustenance activities but a greater proportion of Out-and-About activities, the catchall category.

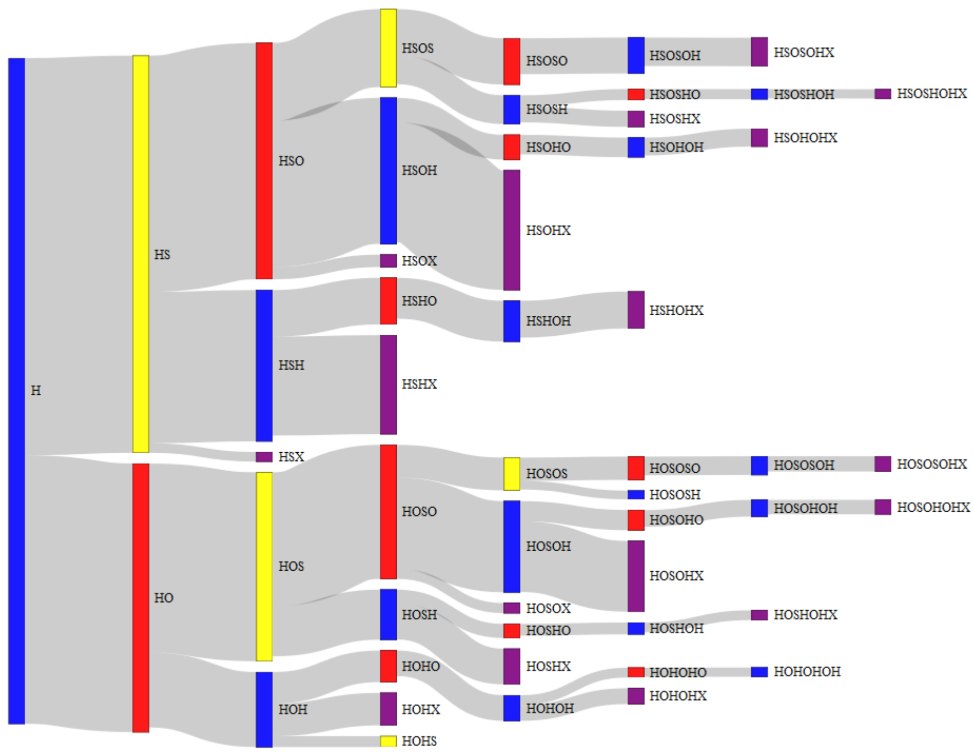


Figure 27: Activity Chaining Plot - Weekday Data

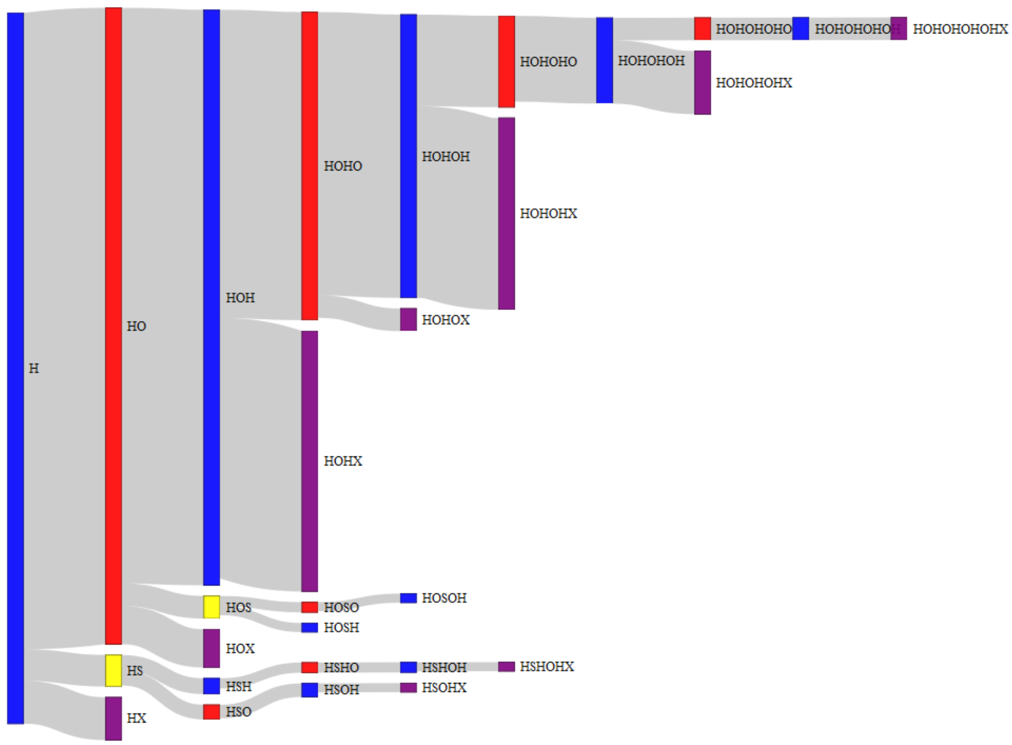


Figure 28: Activity Chaining Plot - Weekend Data

These activity chain representations are limited by the lack of activity duration data. Further, the Out-and-About category contains several different activities (e.g., Shopping, Eating Out, Personal Business). This generalization creates more homogeny than what likely exists. In the stratified plots, the absolute number of observed chains for each stratification group is different. While a different number of chains is used to construct the plots, the plots are still comparable because the pruning technique is based off of proportions instead of an absolute count. When interpreting the figures, care must be taken in constructing stories for what the trip chains represent. For example, a chain of HSH can have a simple interpretation of a person starting at Home, going to Work and then coming Home. While this is an accurate statement, this story may inadvertently imply an amount of time spent doing each activity. HSH could represent a person who spends a full day at Work or a person who only makes a short stop at Work before going back Home. These situations are quite different but both represented by the activity chain HSH. How to incorporate these intricacies is a topic of ongoing research.

CHAPTER 8: DISCUSSION AND CONCLUSIONS

This project developed a smartphone-based behavior intervention tool that provides user-centered messages and graphics to promote travel mode shifts from driving to more sustainable modes. The tool was tested among University of Minnesota (UMN) parking contract holders with three purposes:

- Examine the daily travel behavior patterns of parking contract holders;
- Assess whether the smartphone-generated alternative travel mode recommendations for car trips are considered reasonable among car commuters and whether car commuters would ever consider trying these recommendations
- Identify factors influencing participants' receptiveness toward alternative travel mode recommendations

The tool is designed to target parking contract holders—one of the most captive groups of car commuters—for sustainable travel behavior changes. One of the advantages of the tool is its ability to make more personalized recommendations based on actual daily travel behavior. For each car trip made by the participant, the tool provides information describing the environmental impacts of the specific car trip and the personal benefits of switching to alternative modes for the specific car trip. Participants are also presented with specific mode shift plans for each of the detected car trips based on the exact trip origin and destination.

The activity-trip data analysis in Chapter 4 illustrates that UMN parking contract holders have a typical Monday through Friday work schedule and travel farther for work than for other activities. Non-work and non-home related activities are common during the week but more so on weekends, which include a higher likelihood of a participant leaving and returning home multiple times in the day. Car is the predominant trip mode while walking accounts for most of the remaining trips made in a day. There is little public transit use regardless of whether trips are made on weekdays or weekends. Some biking occurs on the weekends.

These patterns are expected from UMN employees who hold parking contracts. The average travel distance for work emphasizes the large region from which UMN draws employees to a central location—the Twin Cities Campus. Although study participants drive a long distance for work, they are able to fulfill other activities closer to home. However, this closer proximity is not associated with more transit, biking, or walking, indicating automobile dependence.

The first phase of the study presented a significant shortcoming. We could not measure whether participants were checking the trip recommendations in the Daynamica app and we could not measure participants' reactions to the recommendations. In Phase 2 of the study, we were able to assess the quality of these recommendations by asking participants whether they thought the recommendation was reasonable and whether they would consider trying it (Chapter 5). Although 92 percent of Phase 2 participants indicated they were interested in using alternative modes during the intake survey, only 36 percent of the trips made by Phase 2 participants were considered reasonable alternative modes when participants were asked by the smartphone-based tool.

Overall, the Transit and Park & Ride recommendations described in Chapter 6 had a longer distance and duration than the actual car trips, on average, reflecting major accessibility gaps between private car transportation and public transportation in the Twin Cities region. Recommendations that had a shorter travel time than the actual car trips were more likely to be considered reasonable.

Besides distance and duration, we identified a few characteristics that can influence the likelihood of mode switching. Participants making frequent stops on their trip to work are less likely to find an alternative travel mode recommendation reasonable or worth trying. Men are less likely to find a recommendation reasonable and worth trying than women. Lastly, participants who leave for work before 7 AM are more likely to consider a recommendation reasonable and worth trying. Future research could further investigate how these characteristics influence mode choice.

The study is admittedly exploratory in nature. The impact assessment of the tool focuses on participants' receptiveness toward alternative travel mode recommendations rather than whether they made actual modal shifts. We did not alter the participants parking contract during the study. While we removed financial barriers to using transit, there were no additional financial incentives to reduce driving. In addition, participants were in the study for just two weeks; this might not be enough time for participants to adjust their behavior. This could also suggest that participants need more than just information regarding trip alternatives to modify their behavior, such as good quality options and a transition stage.

As an additional undertaking, this project develops a novel method for illustrating participant activity throughout the day to generate comparisons between different demographic and behavioral characteristics. The activity chaining analysis in Chapter 7 depicts the sequence of participant activities greater than 30 minutes. Our analysis illustrates a slight difference in activity patterns between men and women in the study. It also illustrates much less variation in activity chains during the weekend than during the week. Future research could explore alternative methods to construct and analyze activity chains.

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