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COVID-19 Implications on Public Tranpsortation: Understanding Post-Pandemic Transportation Needs, Behaviors, and Experience

Final Report

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The COVID-19 pandemic and widespread social distancing measures have dramatically reduced public transit ridership, leaving transit agencies with massive revenue shortfalls, and it is still unclear how long it will take for transit to recover and whether transit will emerge fundamentally transformed for better or worse after the pandemic. This research collected first-hand data on people's post-pandemic travel behavior decision-making process in the Twin Cities metropolitan region between March and June 2021. Participants were recruited through various forms of digital marketing tools such as a website, social media, emails, and online videos. Of the 339 participants who were enrolled in the study, 154 (45%) used a smartphone app to capture daily transportation needs, behaviors, and experiences for two consecutive weeks. The data provided insights into how the COVID-19 pandemic has shaped people's attitudes, perceptions, and decisions toward various transportation services, including public transportation, and how the mobility impacts of COVID-19 differ by individual socio-demographics and trip environments. Results from this research will help transportation planners identify innovative and sensible ways to effectively promote the use of public transportation in the post-pandemic era.

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COVID-19 IMPLICATIONS ON PUBLIC TRANSPORTATION: UNDERSTANDING POST-PANDEMIC TRANSPORTATION NEEDS, BEHAVIORS, AND EXPERIENCES

FINAL REPORT

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CHAPTER 1: INTRODUCTION

Across the world, many cities and states have issued travel advisories, “shelter-in-place” mandates, and even quarantine orders in an effort to combat the rapid spread of COVID-19. The impacts of these social distancing measures on people’s travel behavior are likely to be long lasting and extend into the post-pandemic era. One such impact could be associating the confined spaces of public transportation with high health and safety risks, leading to future avoidance of public transportation.

On April 2, 2020, the U.S. Department of Transportation’s Federal Transit Administration announced a total of $25 billion in federal funding allocations via the Coronavirus Aid, Relief, and Economic Security (CARES) Act to help public transportation systems around the nation cope with the COVID-19 crisis. Funding was provided at a 100-percent federal share, with no local match required, and will be available to support capital, operating, and other expenses. Many transit agencies were expected to restore the pre-pandemic service levels as soon as the disease outbreak was contained with these federal funding commitments. However, service restoration does not necessarily mean ridership restoration. The pandemic could fundamentally change people’s perception of public transportation so they view it as a less desirable transportation alternative.

Locally, Twin Cities Metro Transit reduced local bus, express bus, and rail transit services during the pandemic, and the agency projected a 50 to 90 percent decline in transit ridership (Metro Transit, 2020). It is critical for the long-term growth and development of transit systems in the Twin Cities region to know whether transit ridership can be restored immediately after COVID-19. Previous research has provided extensive empirical evidence that a robust regional transit system is necessary to foster environmental sustainability, economic prosperity, and social equity in the region (Guthrie et al., 2019; Fan et al., 2016; Fan & Guthrie, 2013; Fan & Tilahun, 2012; Fan et al., 2010). Many government agencies at the local, regional, and state levels have long-term interests in developing a robust regional transit system in the Twin Cities metropolitan region. These agencies include, but are not limited to, the city of Minneapolis, Hennepin County, the Metropolitan Council, and the state of Minnesota. Falling ridership and COVID-19 could alter public support of public transit, preventing the allocation of funds and prioritization of policies needed for high-quality transit services, creating a vicious cycle of underutilization and underinvestment in public transportation.

This research aims to collect original data on how COVID-19 could be shaping the travel behavior decision-making process among downtown Minneapolis commuters at the individual and trip levels. Downtown Minneapolis commuters are one of the largest groups of potential transit users in the region because a vast majority of transit routes in the Twin Cities converge at downtown Minneapolis stations. Understanding the travel behavior decision-making process in response to COVID-19 of these commuters is a critical step in identifying innovative and timely strategies for local transit providers to regain their market share and ridership once the COVID-19 pandemic has ended.

This research recruited a sample of downtown Minneapolis commuters and collected detailed travel behavior decision-making data at the individual trip level in spring 2021, about one year after the start of the COVID-19 pandemic in Minnesota. Recruitment and data collection was conducted virtually without any in-person interactions. Various digital marketing and communication tools were used. Travel behavior decision-making data was collected with a customized mobile app on the participants' smartphones.

The smartphone app is based on the Daynamica app (Fan et al., 2017), a patented technology developed by members of this research team. The app can semi-automatically collect daily activity-travel behavior data with high accuracy and a minimal respondent burden. The surveying capability of Daynamica was customized to examine:

- How users make decisions about each trip, including whether it is made/cancelled, and which transportation modes are selected?
- How do their COVID-19 experiences play a role in shaping these trip decisions?

Most studies examining mobility impacts of COVID-19 use secondary smartphone location data to quantify the amount of travel reduction in response to the COVID-19 crisis. Although informative, such data did not have the granularity and level of detail to uncover the underlying travel behavior decision-making process. How COVID-19 affects travel behavior decision-making may differ greatly by personal socio-demographics and trip environments. This research will help identify inter- and intra-individual differences in the mobility impacts of COVID-19 by collecting primary travel behavior decision-making data from individuals with varied socio-demographics and across multiple trip environments. The findings will help transportation planners identify innovative and sensible ways to promote the use of public transportation in the post-pandemic era.

The report is laid out as follows. Chapter 2 is a review of existing research examining how the COVID-19 pandemic is affecting travel behavior and public transit use in the United States as of May 2022. Chapter 3 describes the study design and recruitment method, including more detail about the use of Daynamica. Chapter 4 presents descriptive statistics from the in-take survey (N=339) including residential location, personal socio-demographics, health-related conditions, and transportation-related conditions, including experiences, attitudes, and preferences toward public transportation. Following the summary statistics, regression models are presented to examine factors contributing to COVID-19-related travel behavior and perception changes.

Chapter 5 presents descriptive statistics from episode characteristics and episode surveys recoded with the Daynamica app (N=154). Episodes include a day, an activity, and a trip. Regression models are tabulated with characteristics from each episode type to examine questions such as concern with COVID-19 and daily travel behavior post-COVID-19. Chapter 6 explores the causal effect of the COVID-19 pandemic on two time-use metrics, using historical Daynamica data collected from a previous study. The first metric summarizes the activity patterns the study population engaged in throughout the day, examining the frequency and ordering of activities. The second metric focuses on the probability of engaging in a certain type of trip or activity throughout the day. Chapter 7 concludes the report. And the appendices with survey instruments are included at the end of the report.

CHAPTER 2: LITERATURE REVIEW

We conducted a review of literature in May 2022 using the University of Minnesota online catalog. We searched for articles that included the terms “public transit,” “COVID-19,” “travel behavior,” and “united states.” We then expanded the number of articles included in the literature review by reviewing articles citing other sources identified by our search terms, using the Web of Science.

Several researchers have begun to investigate the travel behavior among transit users after the onset of the pandemic to better understand the nuances of the observed reduction in overall use. Researchers typically observed anonymized data from smartphones or transit boarding data to analyze trip behavior in comparison with neighborhood- or county-level socioeconomic statistics (Brough et al., 2021; Kim and Kwan, 2021; Liu et al., 2020). Some researchers conducted surveys either to compare to the smartphone data collected (Parker et al., 2021) or analyze alone (Ozbilen et al. 2021; Palm et al., 2021).

Researchers using data from across the U.S. found a greater trip reduction among transit riders compared to non-riders over the course of 2020 (Parker et al., 2021). Researchers investigating travel patterns in King County, Washington, found that there was a greater decline in transit trips than overall trips including all modes; transit trips also rebounded at a slower rate than overall trips throughout 2020 (Brough et al., 2021). There was more mode shifting from transit to cars observed in more educated neighborhoods compared to other neighborhoods in King County (Brough et al., 2021). Researchers using data from the transit trip planning app named Transit observed a greater reduction in trips in cities with higher rates of high tech use (e.g., San Francisco). Research has demonstrated that people are more likely to perceive a greater risk of COVID-19 infection while using shared or high-occupancy modes compared to more private modes (Ozbilen et al., 2021; Shamshiripour et al., 2020); however, perceived risk of infection does not appear to be the only factor accounting for observed travel patterns during the pandemic.

Several researchers identified socioeconomic disparities in how the pandemic affected travel behavior and public transit use. There was a smaller trip reduction among lower-income transit riders compared to higher-income riders (Brough et al., 2021; Parker et al., 2021; Simons et al., 2021). This unequal trip reduction was still present when looking within transit routes, suggesting that service reductions do not solely account for this difference (Brough et al., 2021). The inequitable availability of telecommuting is another important factor in creating this difference (Brough et al., 2021; Liu et al., 2020). Liu et al. (2020) observed this difference between U.S. cities, finding a greater trip reduction in cities with higher rates of non-physical occupations or universities. Kim and Kwan (2021) observed that lower-income people traveled more across all modes during the pandemic. Lower-income people are more likely to be classified as essential workers and have in-person occupations (Kim & Kwan, 2021; Liu et al., 2020)

Simons et al. (2021) was unable to find a significant correlation between rates of COVID-19 and transit demand, suggesting a greater importance of socioeconomic factors. Transit-dependent users were observed to have a more inelastic demand of transit and other shared mobility resources despite the threat of COVID-19 (Wang et al., 2022; Zhou et al., 2021). Transit riders are generally more likely to have lower income, live in an urban area, live in multi-unit buildings, and lack car access compared to the general U.S. population (Liu et al., 2020; Parker et al., 2021).

These socioeconomic differences in overall transit use are also present in new daily patterns of transit use. The reduction in commuting trips among higher-income riders eliminated observable commuting peaks in transit use through the day (Liu et al., 2020; Meredith-Karam et al., 2021). Less-educated neighborhoods and lower-income riders retained visible commuting peaks (Brough et al., 2021). There was also a reduction in non-essential weekend trips among higher-income riders, creating more noticeable commuting peaks in transit use on the weekends, generated by lower-income riders (Liu et al., 2020).

Simons et al. (2021) observed unequal overall transit trip reductions when looking at trip purposes as well. Social, recreation, and worship destinations saw the greatest reductions while shopping and work destinations saw the smallest reductions (Simons et al., 2021). An examination of paratransit services in the Seattle, Washington region found a substantial reduction in work-related and non-essential trips while most remaining trips were medical-related (Wang et al., 2022). Consumer demand for in-person amenities remained low throughout 2020 after the initial shutdowns, suggesting that consumer demand will not return to pre-pandemic levels simply by lifting COVID-19 related restrictions (Sevtsuk et al., 2021). Marlow et al. (2021) also observed that overall neighborhood isolation increased during the first few months of the pandemic. Trips to central business districts especially declined (Marlow et al., 2021; Meredith-Karam et al., 2021). Their findings suggest that mobility was more constrained to neighborhoods (census tracts) more similar to one's own neighborhood (Marlow et al. 2021).

The groups encountering transportation barriers prior to the pandemic, including women and people in poor health, were observed to be more likely at a disadvantage during the pandemic while avoiding public transit (Palm et al. 2021). Palm et al. (2021) observed that lack of access to transportation modes besides public transit was the strongest predictor for a transit rider reporting transportation disadvantage, including lack of vehicle access, poor walkability, and lack of support within the community (Palm et al., 2021). One logistic regression of transit demand found that being a female, having more kids, and being married had a significant correlation with a greater reduction in trips (Simons et al., 2021). This research adds to this body of research by further examining how the mobility impacts of COVID-19 differ by individual socio-demographics and trip environments within the context of the Twin Cities.

CHAPTER 3: STUDY DESIGN AND DATA COLLECTION

This chapter outlines the method used to collect first-hand data on individual behaviors, perceptions, and preferences relating to daily transportation needs in the Twin Cities metropolitan region between March and June 2021, which is after the outbreak of the COVID-19 pandemic. The collected data is expected to have the granularity and level of detail to examine 1) the impacts of COVID-19 on mobility behaviors, perceptions, and preferences; and 2) the sensitivity of the COVID-19 impacts to personal socio-demographics and trip environments.

3.1 SURVEY INSTRUMENTS

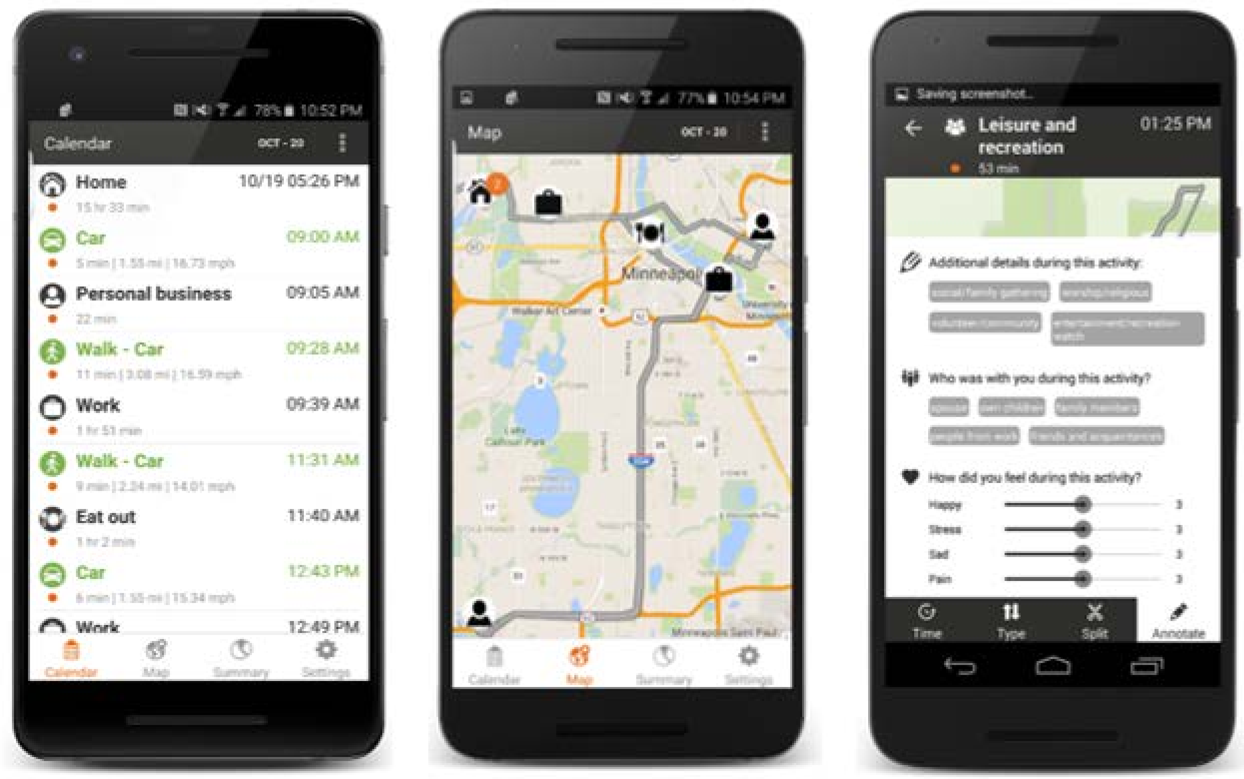
This study utilizes two survey instruments to collect digital data from participants without any in-person interactions amid the social distancing needs throughout the first year of the pandemic. The two survey instruments are:

- an Intake Survey administered via Qualtrics that collects standard demographic information and general information about participants that does not change on the day-to-day level; and
- a smartphone-based, in-app survey administered via the Daynamica app that combines mobile sensing with human input to collect objective and subjective mobility data at the participant-day level for 14 consecutive days.

The Intake Survey asks questions about participant-level attributes that do not vary daily. These attributes can be categorized into three major groups: socio-demographic background, health- and COVID-19-related conditions, and transportation-related attributes. A full listing of questions included in the Intake Survey can be found in Appendix 1.

The smartphone-based, in-app survey asks questions about activities and trips for 14 consecutive days. The Daynamica app employs a digital day reconstruction system that utilizes mobile sensing to derive sequenced activity and trip episodes with higher data accuracy and lower respondent burden than the traditional, recall-based day reconstruction method (DRM) (Fan et al, 2017; Kahneman et al., 2004). Specifically, the app utilizes various location and motion sensors in the smartphone to generate speed, position, and acceleration data at regular time intervals and then employs patented algorithms (Fan et al., 2017) to automatically segment time series into activity and trip episodes in real time throughout the day.

In addition to automated reconstruction of daily activity and trip episodes based upon mobile sensing data, the app allows participants to provide information that are not detectable by mobile sensing (e.g., the preferred transportation mode for a particular trip, trip companionship, and trip experiences). Figure 1 shows the main interface of the Daynamica app, including how the app displays the temporal and spatial information of the automatically reconstructed activity and trip episodes as well as how the user can interact with the app at their convenience to provide additional information about the reconstructed activity and trip episodes.



(a) Daynamica constructs the activity-trip sequence in real time from mobile sensing data, inferring activity/trip start/end time, activity type, and trip mode.

(b) Daynamica captures and displays detailed spatial information of each activity/trip, including activity locations and trip trajectories.

(c) User can interact with Daynamica to confirm or correct activity/trip inferences, and provide additional info (e.g., subjective experience) about each activity/trip.

Figure 1: Main Daynamica Interface.

The in-app survey has multiple advantages:

- It allows the integration of mobile sensing data to generate temporal and spatial information of daily activities and trips, which reduces respondent burden.
- It allows episode-level questions. The reconstruction of activity and trip episodes facilitates the provision of contextualized survey questions at the activity or trip episode level. That is, while the same questions can be asked for each activity or trip, the app could also ask a tailored set of questions for any specific types of activities and trips.
- It allows the incorporation of day-level survey questions to ask about any aspects of daily life that either suppress or reduce demands for transportation. For example, whether the participant has any unmet transportation needs (e.g., any trip cancelations during the day) or any activities accomplished without physical travel (e.g., telework and online shopping).

- It allows the incorporation of exit survey questions, i.e., questions asked at the end of 14 days of data collection.

Details about the in-app survey questions are provided in Appendix 1 which includes episode-level questions, end-of-day questions, and exit survey questions.

3.2 PARTICIPANT RECRUITMENT

Due to COVID-19 concerns in the spring of 2021, study recruitment was performed remotely with no in person contact. The target population for the study were individuals who live in the Twin Cities Metropolitan area. Alongside this, the study aimed to have a diverse sample that included racial minorities. The specific inclusion criteria for the study were that participants needed to be 18 years of age or older, live in the Twin Cities Metropolitan area, and have a smartphone capable of running the Daynamica smartphone app. Participants who completed the 14-day data collection requirement received a $40 electronic Amazon gift card.

The primary recruitment method for the study was through Facebook advertisements. Advertisements were targeted toward individuals 18-65 years of age, living within 25 miles of Minneapolis. Targeted advertisements were also made toward individuals who Facebook identified as having expressed interests in public transportation. Figure 2 illustrates a couple of the Facebook advertisements used in the study. The text was standardized across all advertisements, but different images were utilized to ensure variety. Facebook handled all of the details related to advertisement distribution once the advertisement design was finalized. The specific format and distribution method of the ads varied. The format was managed by Facebook algorithms to maximize outreach while minimizing costs. The advertisement directed participants to the study website, https://cti.umn.edu/, where additional study information was available along with the link to the Intake Survey hosted by Qualtrics.

Our study set a daily spending budget of $5 per day, resulting in an average of about 1,250 impressions (advertisement views) across 1,000 unique individuals per day. On average, 5 to 10 individuals completed the Intake Survey per day. Because of attrition, our overall costs were around $1.50 per completed participant.

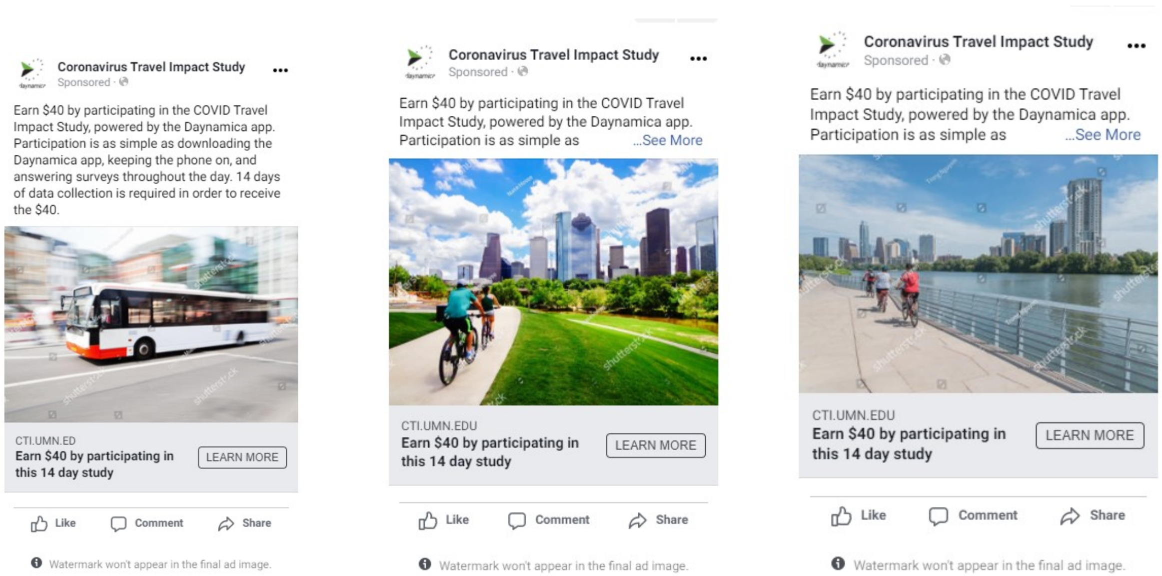


Figure 2: Screenshots of the Facebook Advertisements.

Facebook advertising was an effective method for recruiting participants quickly but failed to yield a sufficiently diverse population of participants to meet study goals. In order to achieve a sufficiently diverse study population, the study switched study recruitment from Facebook advertisements to market research panels managed by Qualtrics on April 30, 2021.

Qualtrics is the world's leading enterprise survey technology solution, which has been providing online samples for over ten years (Qualtrics, 2019). Specifically, Qualtrics partners with over 20 online sample providers to supply a network of diverse, quality respondents. The majority of Qualtrics samples come from traditional, actively managed, double-opt-in market research panels. Qualtrics Research Services allowed the study to target specific demographics for recruitment. The Facebook recruitment strategy resulted in primarily White and Asian women as participants; for the Qualtrics recruitment, we focused on recruiting men of any race and women who were of a race other than White or Asian. This recruitment method was able to achieve a more diverse pool of participants in line with the study objectives.

Table 1: Participants' Gender and Race Representations by Recruitment Method

	Overall		Facebook Recruitment		Qualtrics Recruitment		P-Value
	N	(%)	N	(%)	N	(%)	
Number of Participants	339	100	239	100	100	100	
Gender (%)							<0.001
Man	132	38.9	52	21.8	80	80.0	
Woman	203	59.9	184	77.0	19	19.0	
Non-binary/Third Gender	2	0.6	1	0.4	1	1.0	
Prefer Not to Answer	2	0.6	2	0.8	0	0.0	
Race (Select all that apply)							
White	265	78.2	200	83.7	65	65.0	<0.001
Black or African American	26	7.7	0	0.0	26	26.0	<0.001
Asian	30	8.8	28	11.7	2	2.0	0.008
Hispanic, Latino, or Spanish Origin	14	4.1	6	2.5	8	8.0	0.044
American Indian or Alaska Native	10	2.9	7	2.9	3	3.0	1
Other race, ethnicity, or origin	6	1.8	4	1.7	2	2.0	1

3.3 DATA COLLECTION

The data collection procedure includes multiple phases. The first phase of participation was the completion of the Intake Survey. Upon completing the Intake Survey and confirming study eligibility, participants received an email with information about how to install the Daynamica smartphone app from the Google Play Store (for Android) or the iOS App Store (for iPhone) and begin data collection. We required participants to collect 14 *Quality Days* of data to be compensated for participation in the study. A *Quality Day* requires at least 80% of the episode-level surveys and the end of day survey are completed by the participant for the day. *Quality Days* were not affected by the frequency with which participants engaged in activities and trips, the types of activities and trips, nor the survey responses. The relevant factors were confirmation of data collected, completion of at least 80 percent of episode-level surveys, and completion of end-of-day surveys.

The Study Manager contacted participants to inform them of their data collection progress and whether anything could be done to improve it throughout the data collection period. These updates helped participants stay on track with data collection, ensure high quality data, and ensure timely completion of the study. For various reasons, participants regularly took longer than 14 days in order to collect 14 *Quality Days* of data. Common reasons for failing to meet the requirements were unfamiliarity with the app and study expectations, being too busy, and technical issues preventing the app from collecting data like lack of proper phone permissions. Participants would be notified via email when they completed the

14-day data collection requirement, at which point they were free to uninstall Daynamica and they would receive an electronic gift card from Amazon.

For some participants, the burden of data collection was too high and they were unwilling to participate after a period of time. These participants withdrew from the study either formally or informally withdrew. Participants that withdrew informally uninstalled the app and stopped responding to communication from the Study Manager. These participants were marked as presumed withdrawn after no new data had been received and three failed communication attempts.

A handful of participants did not withdraw from the study nor meet the study requirements for data collection. In these cases, participants were dropped from the study for non-compliance after three repeated attempts to help improve their data collection. These participants were informed that they had been dropped from the study and were free to uninstall the app; data collection was also remotely terminated to ensure no unnecessary data was collected.

Figure 3 shows the rates of attrition and overall trajectory of individuals who completed the Intake Survey. Overall, 239 (70.5%) individuals were recruited via Facebook and completed the Intake Survey; and 100 (29.5%) individuals were recruited via Qualtrics and completed the Intake Survey. Of the individuals who completed the Intake Survey, only 246 (72.3%) installed Daynamica. The 94 (27.7%) who did not did not install the app were labeled as email non-responders. Of those who installed Daynamica, 11 (3.2%) did not upload any data and were presumed to have uninstalled the app prior to the first data upload; 17 (5.0%) participants were dropped from the study for non-compliance; 23 (6.8%) participants formally withdrew; and 40 (11.8%) were presumed withdrawn after data collection stopped and they failed to respond to communication attempts. The remaining 154 participants (45.4%) completed data collection and all the required tasks.

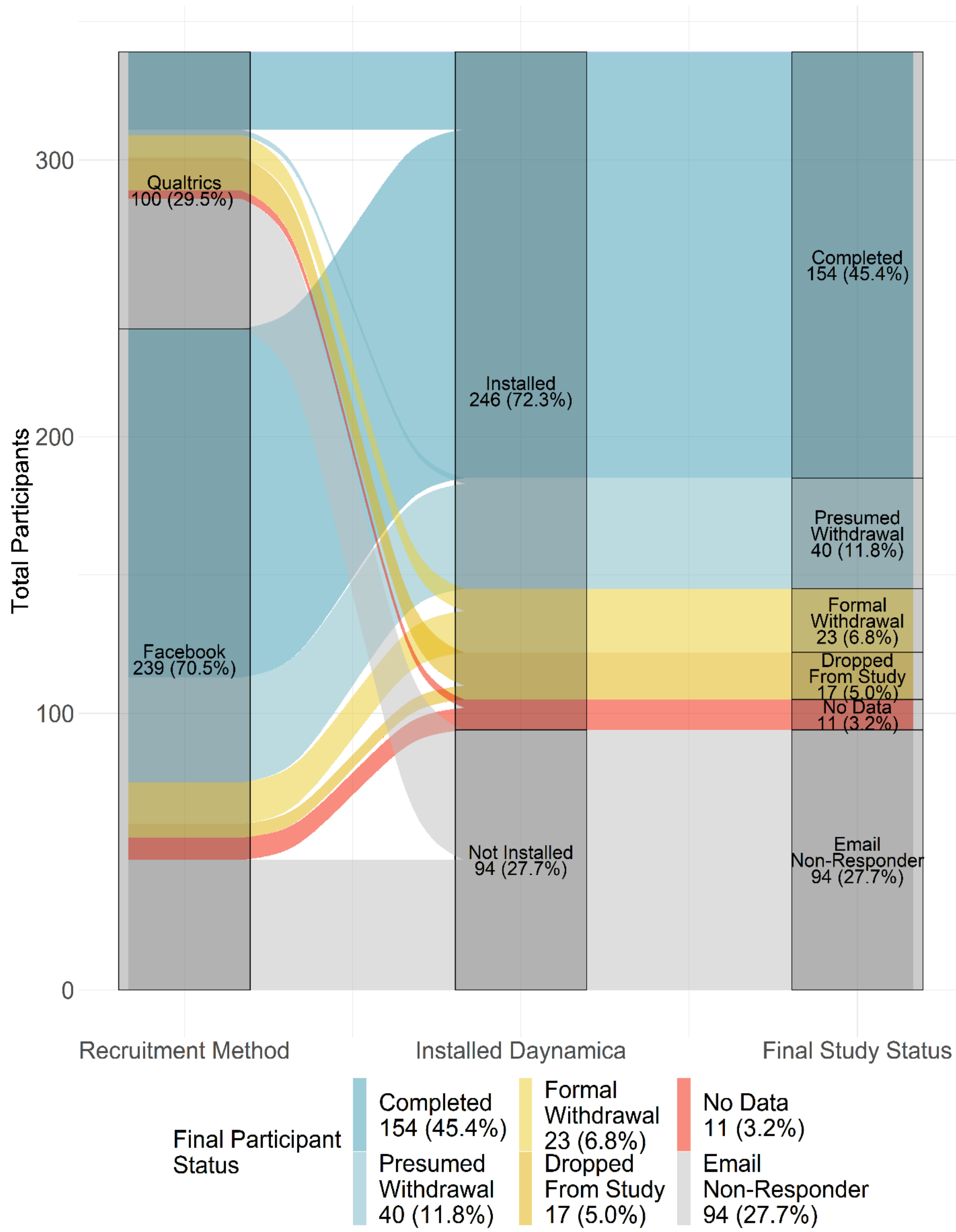


Figure 3: Participant Attrition and Final Participant Status

Figure 4 shows the trajectory of data collection over time, between February 2021 and June 2021. The red line indicates the cumulative number of individuals who were enrolled in data collection activities. Individuals were considered enrolled in data collection activities if they completed the Intake Survey. Enrollment via Qualtrics began April 30th; only 6 participants were recruited via Facebook following the start of recruitment via Qualtrics. Plateaus in the enrollment trajectory occurred during brief pauses in recruitment procedures to ensure sufficient time to monitor and assist participants with data collection.

The blue line of Figure 4 refers to the cumulative total number of participants who completed data collection activities over time. The noticeable delay between when participants are first enrolled and when the first participant completes data collection is due to time it took to complete the 14-day data collection requirement which often required 14 to 21 days of effort. The rate of growth for the Completed Data Collection curve is noticeably slower than the Enrolled curve because of attrition from withdrawals, non-responders, and dropped participants.

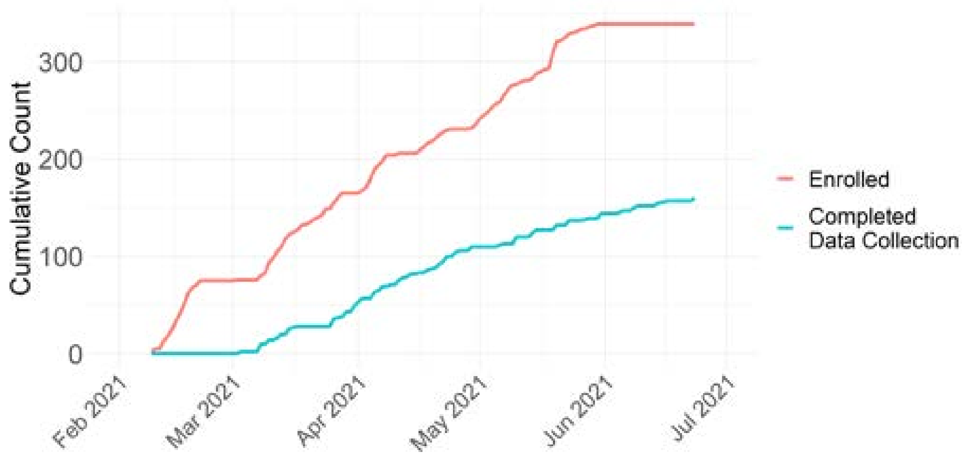


Figure 4: Participant Enrollment and Completion of Data Collection Over Time

3.4 SUMMARY

A total of 339 participants completed the in-take survey. Of these participants, 154 completed the intensive 14-day smartphone-based data collection effort. Both participant recruitment and data collection were done virtually without any in-person interactions amid social distancing needs throughout the first year of the pandemic.

Data collection had to proceed in a brand-new manner given the unprecedented changes in environment during the early stages of the COVID-19 pandemic. Previously, data collection would have included a handful of in-person interactions. Though the study was successful overall, this change in protocol presented new challenges.

A key insight from this study is the high rate of drop-off in participation. Study teams conducting entirely remote procedures must be prepared to overenroll to accommodate study attrition, potentially by a large margin. As seen in Figure 3, study attrition was quite prevalent. We experienced a 25 percent attrition rate between the Intake Survey and participants installing Daynamica. Following this, we experienced an additional 40 percent attrition rate for participants who installed the app. This 40 percent is likely higher than many other studies because of the high burden of data collection compared to the compensation. We suspect that studies with less stringent data collection requirements or who compensate participants more will have a lower rate of attrition.

Understanding these attrition rates are crucial for proper budget and timeline management. A similar fully remote study which aims for 100 completed participants should recognize that they may need to recruit between 150 and 200 participants to reach their goal.

When budgeting, it is important to recognize which study expenses are contingent upon study completion and which expenses are not. Participant compensation was a fixed expense, only paid when participants completed data collection. Facebook advertisements were a fixed expense at a fixed cost per day, regardless of the number of individuals who completed the Intake Survey, started data collection, or completed data collection. Qualtrics recruitment were a variable expense, costing around \$5–15 per individual who completed the Intake Survey (costs vary depending on required demographic makeup of participant pool); we were required to pay for completed Intake Survey responses even if they did not even start data collection with Daynamica. While significantly more expensive, Qualtrics ensured a sufficiently diverse participant pool compared to the cheaper convenience sampling approach through Facebook advertisements.

CHAPTER 4: STATISTICAL ANALYSES OF PARTICIPANT-LEVEL DATA

This chapter summarizes various study participant attributes, including residential location, personal socio-demographics, health-related conditions including concerns towards COVID-19, and transportation-related conditions including experiences, attitudes, and preferences towards public transportation. Following the summary statistics, regression models are presented to examine factors contributing to post-COVID-19 travel behavior, perceptions of hardships, work commute mode choice, travel mode preferences, transit improvement preferences, and attitudes towards transit.

4.1 STUDY AREA AND PARTICIPANT DISTRIBUTION

A total of 339 Twin Cities commuters completed the Intake Survey using Qualtrics. Figure 5 illustrates the residential locations of the Intake Survey participants, aggregated by zip code. Most participants (97%) reside in the 7-county Twin Cities metropolitan area. Of the 326 Twin Cities metro residents, 34% reside in the two central cities—cities of Minneapolis and St Paul.

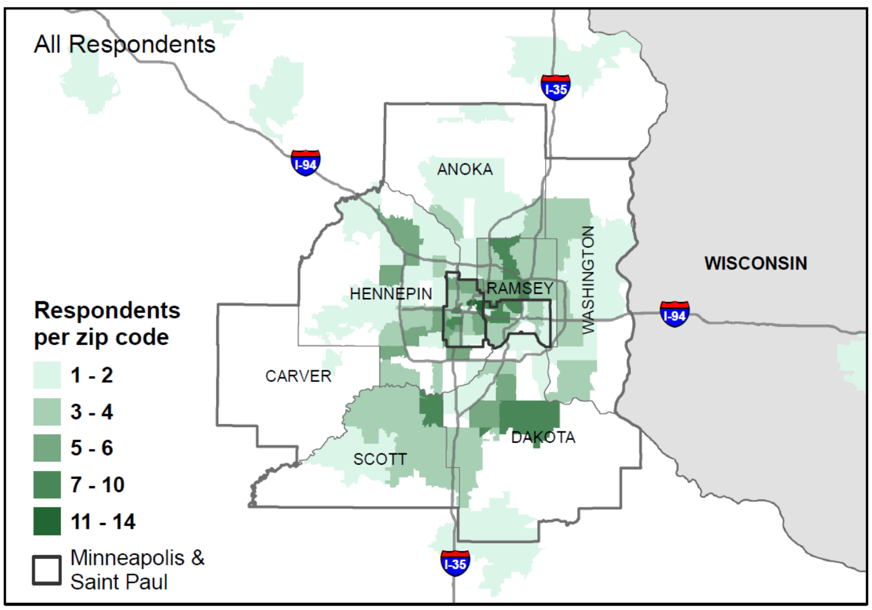


Figure 5: Residential distribution of participants who completed the Qualtrics Intake Survey (N=339 participants).

As described in Chapter 3, less than half of Intake Survey participants (45%) met the study requirements for adequate app-based data collection. The residential distribution of the participants who met the 14-day data collection requirements is illustrated in Figure 6. Of the 154 participants, 149 (97%) reside in the 7-county Twin Cities metropolitan area, including 58 residents (38%) from the two central cities.

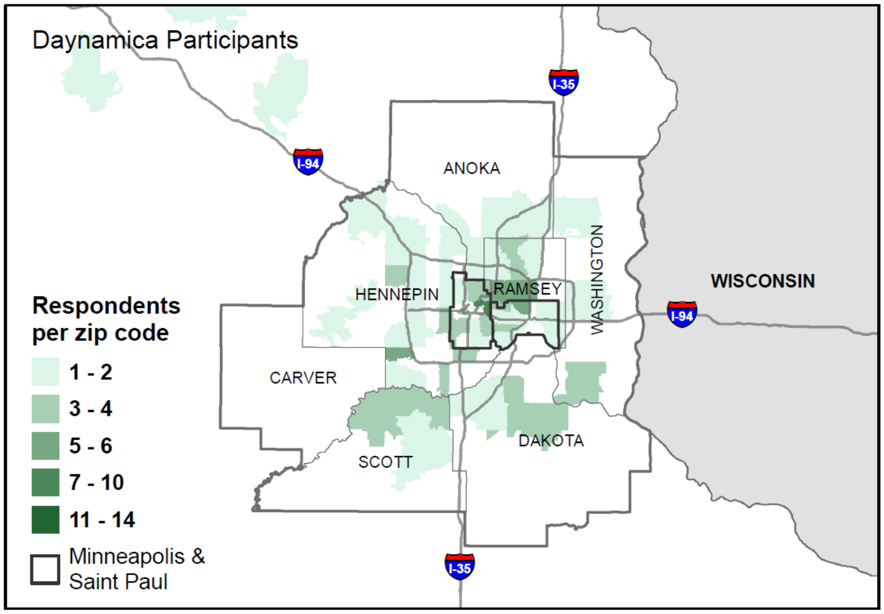


Figure 6: Residential distribution of participants who met the 14-day app-based data collection requirement (N=154 participants).

4.2 SOCIO-DEMOGRAPHIC CHARACTERISTICS

Table 2, below, summarizes socio-demographic characteristics of the two study samples, including information on gender, age, race and ethnicity, education, employment, family structure, housing conditions, and household income levels. As shown in Table 2, the Intake Survey sample (N=339) includes 60 percent female, 25 percent people of color, 70 percent people with bachelor's degree or higher education levels, 60 percent full-time employees, 39 percent essential workers, 30 percent had new jobs or lost jobs, 20 percent had pay-related changes, and 68 percent are homeowners.

Compared to the Intake Survey participants, the subset of the participants who completed the 14-day app-based data collection using the Daynamica app has significantly higher proportions of people with higher education levels as well as people who live with spouse. There is no significant gender, age, employment, income, and housing differences between the two study samples. More detail regarding socio-demographic characteristics is provided after Table 2.

Table 2: Socio-demographics of the two study samples

	Intake Survey Sample (N=339)		Daynamica App Sub-sample (N=154)		P-Value
	N	%	N	%	
Gender					0.630
Male	132	38.9	53	34.4	
Female	203	59.9	99	64.3	
Non-binary/other	4	1.2	2	1.3	
Age					0.402
Young (age 18-30)	84	24.8	30	19.5	
Mid-age (age 30-60)	212	62.5	105	68.2	
Old (age 60+)	43	12.7	19	12.3	
Race and Ethnicity					
White only	253	74.6	126	81.8	0.101
Black or African	26	7.7	3	1.9	0.022
Asian	30	8.8	17	11	0.547
Hispanic, Latino, or Spanish Origin	14	4.1	4	2.6	0.561
American Indian or Alaska Native	10	2.9	2	1.3	0.431
Other	6	1.8	2	1.3	1.000
Education					0.015
High School or Less	31	9.3	8	5.2	
Some College	69	20.6	19	12.3	
Bachelor's Degree or more	235	70.1	127	82.5	
Post-COVID-19 Employment					0.926
Full time	203	59.9	95	61.7	
Part time	54	15.9	23	14.9	
Unemployed/other	82	24.2	36	23.4	
Essential Worker	133	39.2	53	34.4	0.333
Pre-COVID-19 Employment					0.884
Full time	214	63.1	100	64.9	
Part time	57	16.8	26	16.9	
Unemployed/other	68	20.1	28	18.2	
Job Change during COVID-19					
New job/layoff/Quit	101	29.8	39	25.3	0.362
Changes in pay/hours	68	20.1	24	15.6	0.290
No change	124	36.6	69	44.8	0.102
Family Structure					
Living alone	57	16.8	23	14.9	0.695
Living with spouse	216	63.7	112	72.7	0.063
Living with children under 6	49	14.5	26	16.9	0.575
Living with children 6-18	78	23.0	36	23.4	1.000
Living with parents	27	8.0	4	2.6	0.038
Household Income in Year 2019					0.670
Less than $25,000	28	8.3	14	9.1	
$25,000 - $49,999	56	16.5	21	13.6	
$50,000 - $99,999	107	31.6	44	28.6	
$100,000 or more	148	43.7	75	48.7	
Home Type					
Own the home	231	68.1	112	72.7	0.358
Single family home	217	64.0	107	69.5	0.279

Time in the Current Home					0.559
After Mar 2020	54	15.9	27	17.5	
Before Mar 2020 & < 5 years	100	29.5	51	33.1	
5+ years	185	54.6	76	49.4	

- **Gender**: The Intake Survey sample and the Daynamica App sub-sample both over represent female respondents compared to the 7-county Twin Cities Metro, which is about 50 percent men and 50 percent women.
- **Age:** The Intake Survey sample slightly underrepresents the older population (age 60+) compared to the two younger age groups. However, the Young group (age 18-30) experienced the greatest drop-off from the Intake Survey sample to the Daynamica App sub-sample; as a result, the Daynamica App sub-sample slightly overrepresents the Mid-age group (age 30-60) compared to the Young and Old group.
- **Race and Ethnicity:** The Intake Survey sample slightly underrepresents people of color. The Intake Survey has 25.4 percent people of color (including people of Hispanic, Latino, or Spanish Origin); whereas, the 2016-2020 5-Year American Community Survey indicates 28.2 percent people of color in the 7-county Twin Cities Metro. Some individual race groups are better represented than others (e.g., Asian). However, due to greater drop-off among people of color between the Intake Survey and the Daynamica App, the Daynamica App sub-sample more so overrepresents White people than the Intake Survey sample.
- **Education:** Both the Intake Survey and the Daynamica App sub-sample overrepresent people with high levels of educational attainment (Bachelor's Degree or more). The 2016-2020 5-Year American Community Survey indicates 45.1 percent of Twin Cities residents have a bachelor's degree or more. (Note that the 5-Year ACS only records educational attainment for individuals 25 years and older).
- **Post- and Pre-COVID-19 Employment:** Within the Intake Survey sample, there were fewer people employed full-time and part-time at the time of the survey compared to pre-COVID-19, about 3 percentage points and 1 percentage point fewer respectively. This change is reflected in the increase in the percentage of Unemployed/other employment status individuals across this time period. About 40 percent of respondents were self-described Essential Workers at the time of the survey. There is little difference between the Intake Survey sample and the Daynamica App sub-sample.
- **Job Change during COVID-19:** Over a third of the Intake Survey sample (36.6 percent) did not experience a job change during COVID-19. Thirty percent experienced a new job, layoff, or departure (e.g., quit) while 20 percent experienced a change in pay or hours at their same job. There are only slight differences in sample distribution between the Intake Survey sample and the Daynamica App sub-sample.
- **Family Structure:** Both the Intake Survey sample and the Daynamica App sub-sample underrepresent single-person households (living alone) and overrepresent married-couple households (living with spouse). The 2016-2020 5-Year American Community Survey indicates about 30 percent of household are single-person and 50 percent of households are married-couple families. Households with children are well represented. Respondents living with a

spouse are more greatly represented in the Daynamica App sub-sample while respondents living with parents are more greatly underrepresented.

- **Household Income in Year 2019:** The income distribution of the Intake Survey sample is well represented of the 2016-2020 5-Year American Community Survey results. Higher income respondents ($100,000 or more) are overrepresented in the Daynamica App sub-sample while lower income respondents ($49,999 or less) are underrepresented.
- **Home Type:** The 2016-2020 5-Year American Community Survey indicates 65.9 percent of households in the Twin Cities are owner-occupied. The Intake Survey sample slightly overrepresents homeowners. The Daynamica App sub-sample is generally representative of the Intake Survey sample.
- **Time in Current Home:** Over half of the Intake Survey sample have been in their home for over 5 years, about 30 percent have been in their home less than 5 years but at least since the start of the pandemic, about 15 percent have been in their home for less than one year (after the start of the pandemic). This distribution is similar in the Daynamica App sub-sample.
- Data from the 2016-2020 5-Year American Community Survey are obtained from Minnesota Compass (mncompass.org), accessed June 2022.

4.3 HEALTH- AND COVID-19-RELATED CONDITIONS

Table 3 summarizes the sample distribution of health- and COVID-19-related variables, including general health and disability status, underlying health conditions, COVID-19 test and vaccine experiences, and perceived COVID-19 threats.

- **Health and Disability:** Close to 90 percent of the Intake Survey sample indicated they have good or very good health. Although just 13 percent indicated fair or poor health, about 25 percent indicated they have an underlying condition putting them at increased risk of sever COVID-19 illness. The Daynamica App sub-sample is representative of the Intake Survey sample, though there was a greater drop-off rate among respondents with disabilities.
- **COVID-19 Test and Vaccine Status:** At the time of the survey, 40 percent of the Intake Survey sample had tested positive for COVID-19. About 30 percent had never taken a test up to this point. Sixty percent of the Intake Survey sample was vaccinated while 6 percent indicated that they passed on an opportunity to receive a COVID-19 vaccine. The Daynamica App sub-sample is representative of the Intake Survey sample.
- **Perceived COVID-19 Threats:** About a quarter of the Intake Survey sample indicated that COVID-19 is a major threat to their personal health while a third of the sample indicated that COVID-19 is a major threat to family health. The Daynamica App sub-sample is representative of the Intake Survey sample.
- **Hardship due to COVID-19:** Upon asking Intake Survey respondents about potential hardships they encountered due to the pandemic, feelings of isolation and emotional hardships were the top two selected hardships (about 60 percent and 40 percent). Financial hardships or feelings of no adequate support were selected the least (22 percent and 15 percent). Less than 10 percent indicated that they experience no hardship at all. The Daynamica App sub-sample is generally

representative of the Intake Survey sample, though there was a greater drop-off rate among respondents that experienced financial hardships. There is no other significant differences in health and COVID-19-related conditions between the Intake Survey sample and the Daynamica app subsample.

Table 3: Health- and COVID-19-related variables in the two study samples

	Intake Survey Sample (N=339)		Daynamica App Sub-sample (N=154)		P-Value
	N	%	N	%	
Health and Disability					0.957
Fair or poor health	43	12.7	19	12.3	
Good health	127	37.5	56	36.4	
Very good or excellent health	169	49.9	79	51.3	
People with disability	38	11.2	10	6.5	0.141
Underlying conditions with increased risks for severe COVID illness	78	23.1	36	23.4	1
COVID-19 Test and Vaccine Status					
Tested for COVID-19	235	69.3	110	71.4	0.714
Tested positive for COVID-19	138	40.7	58	37.7	0.588
Vaccinated for COVID-19	202	59.6	96	62.3	0.632
Unvaccinated but had Opportunity to be Vaccinated	20	5.9	8	5.2	0.918
Perceived COVID-19 Threats					
Major threat to personal health	89	26.3	41	26.6	1
Major threat to family health	120	35.4	50	32.5	0.595
Hardship due to COVID-19					
Financial	73	21.5	22	14.3	0.077
Emotional	133	39.2	57	37	0.712
Feelings of isolation	201	59.3	93	60.4	0.896
Feelings of no adequate support	49	14.5	16	10.4	0.275
No hardship	29	8.6	14	9.1	0.981

4.4 TRANSPORTATION ATTRIBUTES

Table 4 summarizes the transportation-related variables, including automobile access, telework behavior, experience with public transit, preferences towards public transit improvements, as well as pre- and post-COVID-19 transportation behaviors. The descriptive statistics of these variables are summarized as below:

- **Automobile access:** Within the Intake Survey sample, 5.3 percent of participants reported no working vehicles in the household, and 19.2 percent of participants reported more drivers than working vehicles. There are no significant differences in automobile access between the Daynamica subsample and the Intake Survey sample.
- **COVID-19-related trip changes**: Seventy six percent of the Intake Survey participants reported less trips in general (i.e., do not leave the house as frequently as before COVID-19). There were more reductions in leisure and recreation trips as well as eat out trips than personal business trips. About

half of the participants reported more teleworking behavior and 38% of the participants reported more solo trips because of COVID-19. Participants in the Daynamica sub-sample are significantly more likely to be engaged in trip reduction behaviors than participants in the survey intake sample.

- **Transit experience and interest**: About 88 percent of the Intake Survey participants had prior experience with public transportation. However, only 12 percent of the participants were interested in increasing usage of public transportation at the time of the survey, compared to 32 percent prior to COVID-19. About 18 percent of the Intake Survey participants were comfortable in using transit at the time of the survey, compared to 36 percent prior to COVID-19.
- **Typical work commute mode**: Within the Intake Survey participants, 289 (85%) participants were employed and reported their typical work commute mode. More specifically, 29 percent of the employed participants reported work from home as their typical commute mode, 45 percent reported personal vehicle, 3 percent reported carpool/rideshare/taxi, 5 percent reported public transit, and 4 percent reported walk/bike/scooter as their typical work commute mode. The Daynamica App sub-sample participants were significantly more likely to work from home compared to the overall Intake Survey sample. However, there were no significant differences in other modes as the typical work commute mode between the Daynamica App sub-sample and the overall Intake Survey sample.
- **Willingness to use**: For daily travel needs (including work and non-work needs), 94 percent of the Intake Survey participants reported willingness to use personal vehicle at the time of the survey, compared to 92 percent prior to COVID-19. Twenty percent reported willingness to use carpool/rideshare/taxi at the time of survey, compared to 33 percent prior to COVID-19; 18 percent reported willingness to use transit, compared to 45 percent prior to COVID-19; and 39 percent reported willingness to use walk/bike/scooter, compared to 41 percent prior to COVID-19. There were no significant significances in the statistics of these variables between the Daynamica App sub-sample and the overall Intake Survey sample when it comes both pre- and post-COVID-19 variables.
- **Desired transit Improvements:** Closer stops to home/destination was reported as the most desired transit improvement, followed by faster travel speeds, safe walking routes to stops, better real time information, more amenities at stops and during wait, and more frequent services. Participants reported less desire in more comfortable buses/trains, transit advantages like bus-only lanes, extended service hours, more reliable service, and lower fare.
- **Desired transit COVID-19 measures:** Increased cleaning frequency was reported as the most desired COVID-19-related transit improvement, followed by limited seating for social distancing, enforcing mask requirement strongly, presence of ambassadors, and live video surveillance. Participants reported less desire in presence of more transit police, contactless payment options, option to text to report issues, and improved boarding/exiting procedures.

Table 4: Transportation-related variables in the two study samples

	Intake Sample (N=339)		Daynamica Sub-sample (N=154)		P-Value
	N	%	N	%	
Automobile Access					
More drivers than working autos	65	19.2	28	18.2	0.891
No autos	18	5.3	9	5.8	0.978
COVID-19-related trip changes					
Fewer trips in general	259	76.4	132	85.7	0.025
Fewer eat out trips	267	78.8	132	85.7	0.09
Fewer personal business trips	189	55.8	102	66.2	0.036
Fewer leisure and recreation trips	253	74.6	127	82.5	0.071
More teleworking	171	50.4	95	61.7	0.026
More solo trips	130	38.3	61	39.6	0.867
Transit Experience and Interest					
Prior experience using transit	298	87.9	137	89	0.852
Interested in more transit use (pre covid)	107	31.6	51	33.1	0.812
Comfortable with transit use (pre covid)	96	36.4	39	34.5	0.821
Interested in more transit use (post covid)	39	12.2	13	8.8	0.352
Comfortable with transit use (post covid)	58	18.4	15	10.2	0.034
Typical Commute Mode (Pre-COVID-19)					
Work from home	21	6.2	12	7.8	0.643
Personal Vehicle	217	81.6	100	84.0	0.661
Carpool/rideshare/taxi	14	8.5	5	7.9	1.00
Public transit	35	19.6	16	22.9	0.685
Walk/bike/scooter	18	10.6	6	9.2	0.947
Typical Commute Mode (Post-COVID-19)					
Work from home	98	28.9	59	38.3	0.049
Personal Vehicle	151	44.5	58	37.7	0.182
Carpool/rideshare/taxi	10	2.9	3	1.9	0.734
Public transit	18	5.3	4	2.6	0.264
Walk/bike/scooter	12	3.5	6	3.9	1
Willingness to Use (Pre-COVID-19)					
Personal Vehicle	311	91.7	143	92.9	0.806
Carpool/rideshare/taxi	111	32.7	52	33.8	0.904
Public transit	154	45.4	79	51.3	0.266
Walk/bike/scooter	140	41.3	68	44.2	0.619
Willingness to Use (Post-COVID-19)					
Personal Vehicle	320	94.4	146	94.8	1
Carpool/rideshare/taxi	69	20.4	25	16.2	0.339
Public transit	60	17.7	25	16.2	0.787
Walk/bike/scooter	131	38.6	65	42.2	0.516
Desired transit improvements					
Closer stops to home/destinations	170	50.1	80	51.9	0.785
Safer walking routes to stops	104	30.7	45	29.2	0.825
More amenities at stops & during wait	97	28.6	45	29.2	0.976
More comfortable buses/trains	67	19.8	29	18.8	0.905
Faster travel speeds	113	33.3	55	35.7	0.679
Transit Advantages like bus-only lanes	54	15.9	21	13.6	0.602
More frequent service	96	28.3	46	29.9	0.806

Extended service hours	70	20.6	35	22.7	0.686
More reliable service	68	20.1	27	17.5	0.592
Better real time information	103	30.4	47	30.5	1
Lower fare	58	17.1	22	14.3	0.512
Desired transit COVID-19 measures					
Increased cleaning frequency	181	53.4	90	58.4	0.344
Enforcing mask requirements strongly	189	55.8	96	62.3	0.203
Presence of ambassadors	104	30.7	56	36.4	0.252
Presence of Metro Transit police	132	38.9	64	41.6	0.651
Limiting seating for social distancing	173	51	90	58.4	0.152
Contactless payment options	156	46	74	48.1	0.747
Live video surveillance	138	40.7	57	37	0.498
Option to text to report issues	105	31	56	36.4	0.281
Improved boarding/exiting procedures	73	21.5	31	20.1	0.814

The enrollment of survey participants took about three months between March and May 2021. Figure 7 shows the rolling average of the weekly precentage of participants who reported being comfortable with transit use over the enrollment period. It is evident that participants who enrolled in the survey in May 2021 reported higher comfort in transit use compared to participants enrolled in March and April 2021. This is not surprising because perceived comfort of transit use is time-dynamic dependent upon factors such as the availability of vaccines and the emergence of COVID-19 variants at the time of the survey. Figure 8 on the next page provides more detail how participants indicated intrest in using transit more and comfort with transit use prior to COVID-19 padnemic and at the time of the survey.

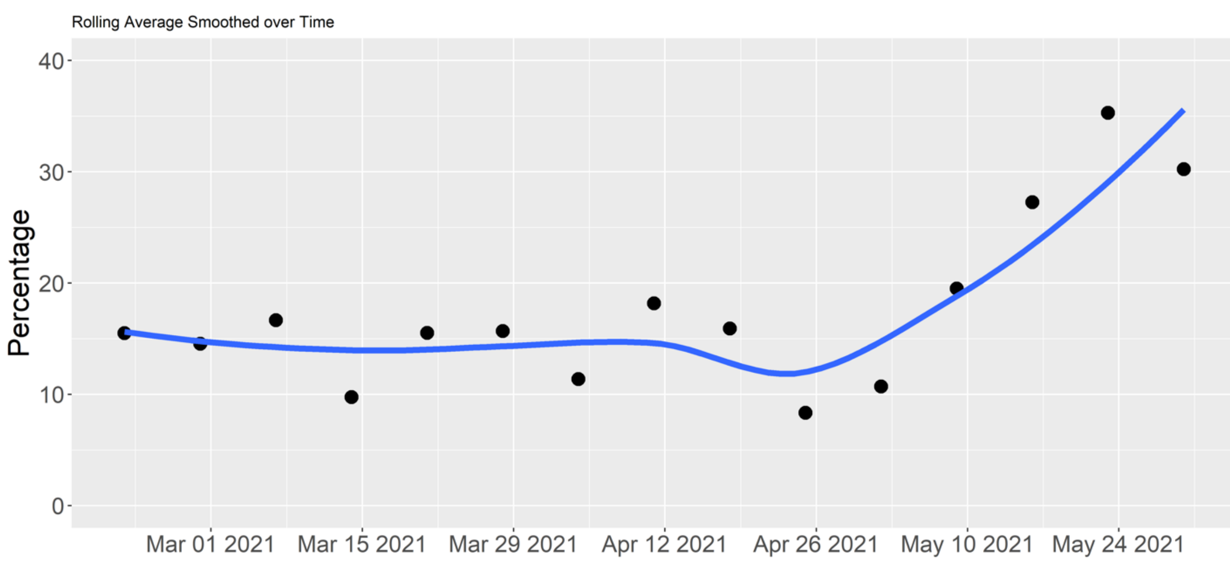


Figure 7: Rolling average of the percentage of participants who reported being comfortable with transit use each week over the entire enrollment period.

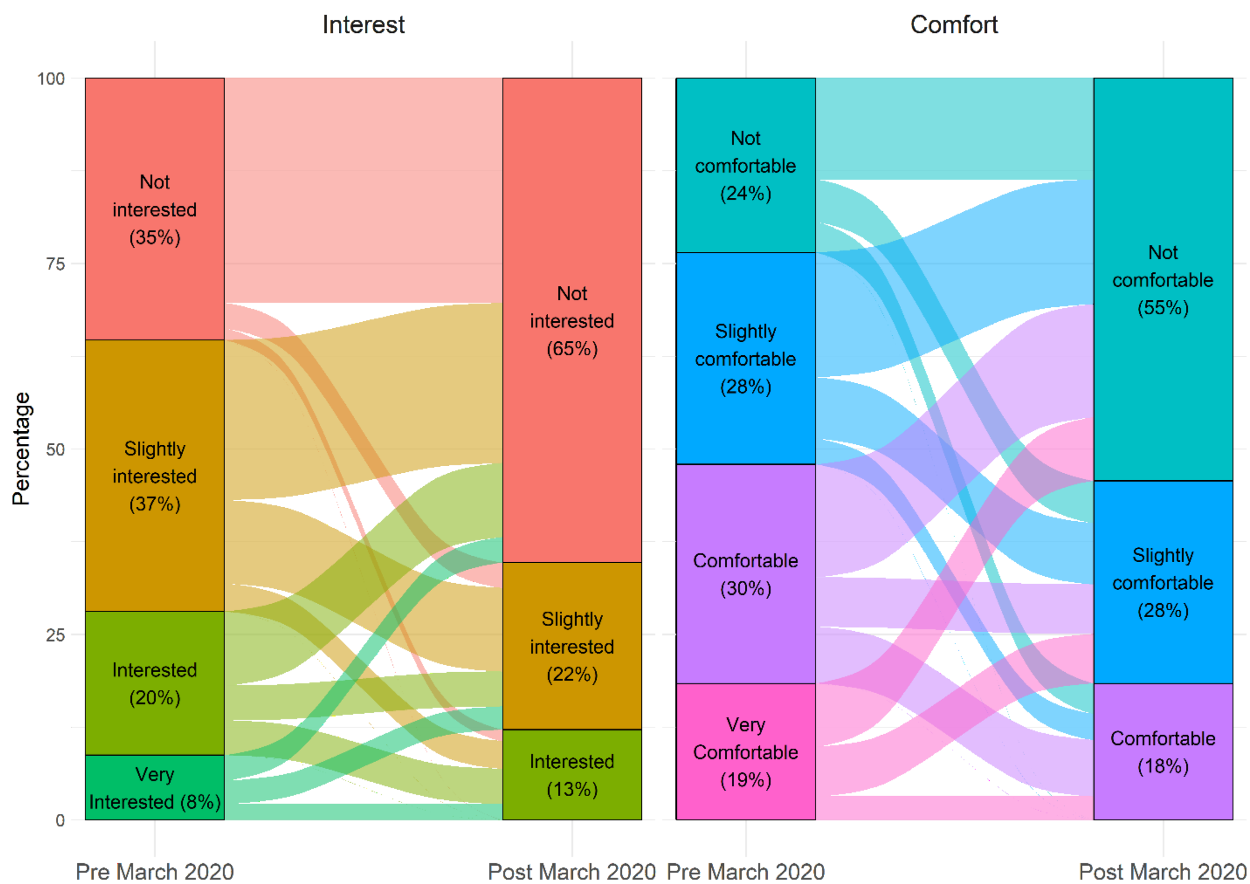


Figure 8: Interest in more transit use and comfort with transit use.

A summary of Figure 8 is detailed below:

- The number of respondents Not interested in using transit almost doubled over the period of before March 2020 to the time of the survey. While 8 percent of respondents were Very Interested in using transit more before March 2020, no one expressed this level of interest at the time of the survey.
- The number of respondents Not Comfortable with transit more than doubled over the period of before March 2020 to the time of the survey. Nineteen percent of the respondents indicated they were Very Comfortable with transit before March 2020 but no one expressed this level of comfort at the time of the survey.
- The changes in interest and comfort are similar; however, there is a greater proportion of respondent moderately comfortable with using transit at the time of the survey. Although, this level of comfort does not translate into a similar level of interest in using transit more.
- There is also a modest number of respondents who become more comfortable or interested in using transit more at the time of the survey compared to before the pandemic.

4.5 REGRESSION MODELS

This section presents a series of logistic regression models that estimate how participant attributes such as personal socio-demographics, family structure, automobile access, and health- and COVID-19-related conditions predict post-COVID-19 behaviors. First, Table 5 details the odds ratio estimates regarding change in time use or trips made.

Table 5: Odds ratio estimates from logistic regression models on COVID-related effects on time use. Columns refer to different dependent variables, rows refer to independent variables.

	Fewer trips in general	Fewer eat out trips	Fewer personal business trips	Fewer leisure & recreation trips	More telework	More solo trips
Intercept	1.478	2.88	0.66	15.198**	0.848	0.377
Socio-demographics						
Female and gender nonconforming	2.122**	1.687°	1.650*	1.785°	1.941*	2.228**
Age 30-60	1.124	1.104	1.179	0.67	0.757	1.664
Age 60+	1.397	4.899°	3.738*	3.406	0.61	5.076**
White Only	0.692	1.133	0.979	1.858	0.989	0.602
Asian	0.751	0.476	0.995	0.748	0.677	0.483
Black	0.251*	0.275°	0.408	0.056***	0.897	0.321°
Bachelor's Degree or More	3.811***	1.596	1.526	1.265	2.293*	0.888
Unemployed/Other	1.409	1.07	0.589	0.512	0.208***	0.847
Essential Worker	0.86	0.576	0.819	0.774	0.330***	0.89
Job changes during COVID-19	1.475	2.297*	1.306	2.458*	0.86	1.710°
Change in Pay/Hours COVID-19	0.964	1.56	1.386	2.286°	1.228	2.108*
Household Income < $50,000	1.282	0.668	0.846	0.294**	1.077	1.323
Homeowner	0.875	0.806	0.762	0.208**	0.875	0.96
Family Structure						
Live w/ Spouse	1.158	0.796	0.923	0.622	1.231	0.826
Lives w/ Child	0.725	0.944	1.061	1.254	1.926*	1.571
Lives w/ Parents	2.715	0.922	2.228	2.339	0.572	0.601
Automobile Access						
More Drivers than Vehicles	0.631	1.233	0.921	0.533	1.849°	0.734
No Working Vehicles	1.598	0.618	0.904	0.391	0.769	1.174
Health- and COVID-related conditions						
Very Good or Excellent Health	0.765	1.202	1.141	0.872	0.884	0.928
Disabled	0.756	0.614	0.813	0.288**	0.966	1.081
Relevant Underlying Conditions	1.141	2.105	0.921	1.361	1.334	0.69
COVID-19 Major Threat to Self	1.616	1.195	3.005***	1.409	0.886	1.088
Tested Positive for COVID-19 Before	0.595°	0.508*	0.733	0.435**	1.011	0.844
Summary Statistics						
N	339	339	339	339	339	339

Pseudo R2	0.135	0.142	0.098	0.23	0.152	0.087

Note: ***p<0.001, **p<0.01, *p<0.05, °p<0.10

A summary of Table 5 is detailed below.

- About 75 percent of the Intake Survey sample indicated they make fewer trips in general, fewer eat out trips, and fewer leisure and recreation trips. About 50 percent of the sample indicated they make fewer personal business trips and telework more. About 40 percent of the sample indicated they make more solo trips.
- Ten sociodemographic variables are statistically significant in predicting change in trip frequencies.
  - Female and gender non-conforming respondents have a positive association with each regression. They over twice as likely to make fewer trips overall but are also over twice as likely to make more solo trips.
  - Respondents aged 60 and older are almost 5 times as likely to have fewer eat out trips, almost 4 times as likely to have fewer personal business trips, and 5 times as likely to make more solo trips.
  - Black respondents have a negative association with 4 of the 6 regressions. They are 75 to 95 percent less likely to make fewer trips overall, eat out trips, and leisure and recreation trips. They are also 68 percent less likely to make more solo trips.
  - Respondents with a bachelor's degree or more are almost 4 times as likely to have fewer trips in general and over twice as likely to telework more.
  - In contrast, essential workers and unemployed respondents are 67 percent and 79 percent less likely to telework more.
  - Respondent that experienced a job change are over twice as likely to make fewer eat out trip and fewer leisure and recreation trips. They are also 71 percent more likely to make more solo trips.
  - Respondents that experienced a pay change are over twice as likely to make fewer leisure and recreation trips and to make more solo trips.
  - Low-income respondents and homeowners are 70 to 80 less likely to make fewer leisure and recreation trips.
- Respondents with children are 93 percent more likely to telework more.
- Respondents in households with more drivers than vehicles were also 85 percent more likely to telework more.
- Health- and COVID-related condition variables are significant in 5 instances.
  - Disabled respondents are 71 percent less likely to make fewer leisure and recreation trips.
  - Respondents that tested positive for COVID-19 are 40 to 60 percent less likely to make fewer trips overall, fewer eat out trips, and fewer leisure and recreation trips.
  - Respondents to whom COVID-19 is a major threat are three times as likely to make fewer personal business trips.

Table 6 details the odd ratio estimates regarding the likelihood that a respondent selects a particular hardship that they experienced due to the COVID-19 pandemic.

Table 6: Odds ratio estimates from logistic regression models on hardships experienced due to COVID-19. Columns refer to different dependent variables, rows refer to independent variables.

	Emotional	Financial	Isolation	No Adequate Support
Intercept	2.696	0.605	1.972	0.740
Socio-demographics				
Female and gender nonconforming	0.941	0.436*	1.233	0.542
Age 30-60	0.64	2.391°	1.125	1.794
Age 60+	0.235**	0.577	1.505	1.87
White Only	0.460°	0.279*	1.002	0.329*
Asian	0.414	0.345	0.545	0.554
Black	0.416	0.396	1.17	0.66
Bachelor’s Degree or More	0.474*	1.193	1.179	0.404°
Unemployed/Other	1.213	4.582***	1.003	1.281
Essential Worker	1.117	1.405	0.496**	1.016
Job changes during COVID-19	1.063	1.848°	0.85	1.426
Change in Pay/Hours COVID-19	2.226*	4.397***	1.397	2.872*
Household Income < $50,000	0.478*	1.139	1.201	0.449°
Homeowner	1.3	0.239***	0.82	0.301**
Family Structure				
Live w/ Spouse	1.424	0.652	1.057	1.042
Lives w/ Child	0.916	1.186	0.822	1.316
Lives w/ Parents	1.181	2.248	0.923	2.805
Automobile Access				
More Drivers than Vehicles	1.534	0.869	1.474	1.311
No Working Vehicles	1.855	0.181°	0.572	0.426
Health- and COVID-related conditions				
Very Good or Excellent Health	0.815	0.656	0.958	0.85
Disabled	1.613	1.48	1.401	6.352***
Relevant Underlying Conditions	0.645	1.468	0.815	0.232*
COVID-19 Major Threat to Self	1.106	0.633	1.012	1.302
Tested Positive for COVID-19 Before	0.608°	1.338	0.553*	0.837
Summary Statistics				
N	339	339	339	339
Pseudo R2	0.099	0.293	0.052	0.267

***p<0.001, **p<0.01, *p<0.05, °p<0.10

A summary of Table 6 is detailed below.

- Feelings of isolation was the most selected hardship (59%). Emotional hardship was selected by 39 percent of respondents and financial hardship was selected by 21 percent. Feelings of no adequate support was selected by the least amount survey participants (15%).
- There are 11 sociodemographic variables that are statistically significant in at least one of the hardship regressions.
    - Female and gender nonconforming respondents are 56 percent less likely to select a financial hardship than male respondents.
    - Respondents aged 30 to 60 are over twice as likely to select financial hardship.
    - Respondents aged 60 and older are 77 percent less likely to select an emotional hardship compared to younger respondents.
    - White respondents are between 50 and 75 percent less likely to select emotional, financial, or lack of adequate support hardships compared to non-white respondents.
    - Respondents with a bachelor's degree or more are 53 percent and 60 percent less likely to select emotional or lack of adequate support hardships compared to respondents with less education.
    - Unemployed respondents are over 4 times as likely to select financial hardship.
    - Essential worker respondents are 50 percent less likely to select isolation hardships.
    - Respondents that experience a change in pay or hours are over twice as likely to select emotional hardship, over 4 times as likely to select financial hardship, and almost 3 as likely to select a lack of adequate support hardship.
    - Similarly, respondents that experienced a job change were almost twice as likely to select financial hardship.
    - In contrast, homeowners were about 75 percent less likely to select financial hardship and lack of adequate support hardship compared to non-homeowners.
- Family structure variables were not significant in any hardship regression
- Just one automobile access variable, no working vehicles, was significant in just the financial hardship regression. Respondents without working vehicles were about 80 percent less likely to select this type of hardship.
- Health- and COVID-19-related conditions were significant in 4 instances.
    - Disabled respondents were over 6 times as likely to select lack of adequate support hardship.
    - Respondents with relevant underlying conditions were 77 percent less likely to select lack of adequate support hardship.
    - Respondents that have tested positive for COVID-19 were 40 to 45 percent less likely to select emotional or isolation hardships compared to respondents who presumably did not have COVID-19 yet.

Table 7 details the odds ratio estimates regarding the likelihood that a respondent is using a particular mode to typically commute to work at the time of the survey.

Table 7: Odds ratio estimates from logistic regression models for typical commute mode to work post-COVID-19. Columns refer to different dependent variables, rows refer to independent variables.

	Personal Vehicle	Car Share	Public Transit	Non-Motorized	Work Form Home
Intercept	8.644**	0.014°	0.037	0.012*	0.038***
Socio-demographics					
Female and gender nonconforming	0.565*	0.431	0.738	0.806	2.328**
Age 30-60	0.543	3.834	0.763	1.428	2.778*
Age 60+	0.47	0	0	0	0.989
White Only	0.639	0.988	0.017***	0.339	1.235
Asian	0.589	0	0.013*	0.164	1.42
Black	0.093**	24.050°	1.075	1.09	6.097*
Bachelor's Degree or More	0.546	0.607	2.228	2.203	2.330°
Unemployed/Other	0.147***	0.946	0.037°	0.197	0.119***
Essential Worker	2.601**	1.653	10.134*	1.474	0.370**
Job changes during COVID-19	0.965	0.217	3.887	1.158	1.142
Change in Pay/Hours COVID-19	1.633	7.237*	0.387	2.142	0.629
Household Income < $50,000	0.542	0.183	4.389°	4.457°	1.575
Homeowner	0.399*	1.584	2.526	2.099	3.306**
Family Structure					
Live w/ Spouse	0.96	0.194	0.191	0.686	1.005
Lives w/ Child	1.810°	1.746	0.336	0	0.62
Lives w/ Parents	3.265°	0.212	0.179	2.234	0.080*
Automobile Access					
More Drivers than Vehicles	0.235**	4.165	47.758**	12.599*	2.005
No Working Vehicles	0.061*	1.6	3.889	5.196	1.494
Health- and COVID-related conditions					
Very Good or Excellent Health	1.856*	0.181	0.051**	1.053	0.782
Disabled	0.348*	0	7.841°	1.094	1.931
Relevant Underlying Conditions	1.324	0.586	3.004	1.245	0.68
COVID-19 Major Threat to Self	0.711	4.393	1.56	0.112	1.424
Tested Positive for COVID-19 Before	0.922	1.424	1.754	0.535	1.366
Summary Statistics					
N	339	339	339	339	339
Pseudo R2	0.283	0.422	0.561	0.378	0.223

A summary of Table 7 is detailed below.

- Almost half of the Intake Survey sample selected personal vehicle for their typical commute mode post-COVID-19 (45%). The next largest group worked from home (29 percent). Five percent or fewer of respondents select carshare, public transit, or non-motorized modes (representing 18 or fewer respondents); the vast majority of respondents were not using these modes to commute typically.

- There are 10 sociodemographic variables that have statically significant results.
  - Black respondents have a positive association with selecting car share, are 6 times as likely to work from home, and 91 percent less likely to commute via personal vehicle.
  - Unemployed respondents are 85 percent less likely to commute via personal vehicle and 88 percent less likely to work from home. Unemployed respondents also have a negative association with commuting via public transit.
  - Essential workers are over twice as likely to commute via personal vehicle and 63 percent less likely to work from home. There is also a positive association with using public transit.
  - Female and gender nonconforming respondents are 44 percent less likely to commute via personal vehicle and over twice as likely to work from home.
  - Respondents with household income less the $50,000 have a positive association with using public transit and non-motorized commute modes.
  - Homeowners are 60 percent less likely to use a personal vehicle and over three times as likely to work from home.
  - Asian and white respondents have a negative association with using public transit to commute.
  - Respondents aged 30 to 60 are almost 3 times as likely to work from home.
  - Respondents that experience a change in pay or hours have a positive association with typically commuting via Car Share.
- Family structure variables were significant in 3 instances
  - Respondents living with children are 81 percent more likely to commute via personal vehicle while respondents living with parents are over three times as likely to commute via personal vehicle.
  - Respondents living with parents are over 90 percent less likely to work from home.
- Automobile access variables were statistically significant in 4 instances, with more drivers than vehicles in a household as a consistent factor.
  - Respondents with more drivers than vehicles in a household are 77 percent less likely to commute via personal vehicle. They also have a positive association with typically commuting via public transit or non-motorized modes.
  - As expected, respondents without access to a working vehicle are over 90 percent less likely to commute via a personal vehicle.
- Two health-related variables were significant in predicting personal vehicle and public transit use.
  - Respondent in good health are 86 percent more likely to commute via personal vehicle. They also have a negative association with using public transit.
  - In contrast, disabled respondents are 65 percent less likely to commute via personal vehicle and have a positive association with using public transit.

Table 8 details the odds ratio estimates regarding the likelihood a respondent is willing to use a particular commute mode at the time of the survey.

Table 8: Odds ratio estimates from logistic regression models for willingness to use commute mode to work. Columns refer to different dependent variables, rows refer to independent variables.

	Personal Vehicle	Car Share	Public Transportation	Non-Motorized
Intercept	1262.561**	0.112*	0.931	0.636
Socio-demographics				
Female and gender nonconforming	0.553	0.956	0.809	1.045
Age 30-60	0.518	0.763	1.634	0.878
Age 60+	2845801	0.429	1.923	1.407
White Only	11.562*	1.554	0.608	0.924
Asian	2.639	1.508	0.217°	0.683
Black	0.582	3.975°	0.888	0.291°
Bachelor's Degree or More	0.236	1.306	0.97	1.657
Unemployed/Other	0.841	1.866	0.647	2.118*
Essential Worker	0.367	1.599	0.984	1.135
Job changes during COVID-19	0.161°	1.642	1.800°	1.062
Change in Pay/Hours COVID-19	1.358	2.197*	1.22	1.267
Household Income < $50,000	0.524	0.879	0.601	1.327
Homeowner	0.828	1.159	0.474°	0.765
Family Structure				
Live w/ Spouse	2.671	0.578	0.344**	0.646
Lives w/ Child	0.964	0.74	1.024	1.217
Lives w/ Parents	0.316	0.676	0.46	0.664
Automobile Access				
More Drivers than Vehicles	0.789	1.451	0.986	1.859°
No Working Vehicles	0.005***	3.775*	7.255**	1.128
Health- and COVID-related conditions				
Very Good or Excellent Health	0.817	0.871	0.875	0.907
Disabled	0.404	2.186	1.06	0.768
Relevant Underlying Conditions	0.561	0.866	1.287	0.847
COVID-19 Major Threat to Self	0.411	0.661	0.478	0.818
Tested Positive for COVID-19 Before	0.187*	1.024	0.767	0.782
Summary Statistics				
N	339	339	339	339
Pseudo R2	0.534	0.13	0.152	0.068

A summary of Table 8 is detailed below.

- Almost all of the Intake Survey respondents indicated a willingness to use a personal vehicle (94%). The next largest groups were willingness to use non-motorized modes (39%) and car share (20%). The least number of participants indicated a willingness to used public transit (18%).

- There are 7 sociodemographic variables that are statistically significant in predicting willingness to use a particular mode.
    - White respondents have a positive association with willingness to use personal vehicle.
    - Asian respondents are almost 80 percent less likely to select public transit
    - Black respondents are about 4 times as likely to select car share and 71 percent less likely to select non-motorized modes.
    - Unemployed respondents are over twice as likely to select non-motorized modes.
    - Respondents that experience a job change have a negative association with willingness to use a personal vehicle but are 80 percent more likely to select public transit.
    - Respondents that experienced a pay change are over twice as likely to select car share.
    - Homeowners are 53 percent less likely to select public transit.
- Family structure variables are significant in just one instance.
    - Respondents living with a spouse are 66 percent less likely to select public transit.
- Automobile access variables are significant in each mode regression.
    - Respondents in households with more drivers than vehicles are 86 percent more likely to select non-motorized modes.
    - Respondents without a working vehicle have a negative association with willingness to use a personal vehicle, are almost 4 times as likely to select car share, and are over 7 times as likely to select public transit.
- Just one COVID-related condition variable is significant in one instance.
    - Respondents that have tested positive for COVID-19 have a negative association with willingness to use a personal vehicle.

Table 9 details the odds ratio estimates regarding the likelihood that a respondent will desire a non-COVID-19 related transit improvement.

Table 9: Odds ratio estimates from logistic regression models for desired non-COVID-19 related transit improvements. Columns refer to different dependent variables, rows refer to independent variables

	Closer Stops	Extended Hours	Faster Service	Lower Fare	More Amenities	More Frequent Service	On Time Service	Real Time Information	Safer walking routes to stop	Transit Advantages	More Comfortable
Intercept	0.649	0.252°	1.906	0.305	1.704	0.615	0.993	0.357	0.349	0.446	0.28
Socio-demographics											
Female and gender nonconforming	1.37	0.694	0.653	0.494°	0.704	0.982	0.629	1.009	1.161	0.557°	0.598°
Age 30-60	0.705	1.017	0.742	0.369*	0.383**	1.035	0.490°	0.727	0.525°	0.623	1.084
Age 60+	1.38	0.999	0.218**	0.100**	0.209**	0.688	0.148**	0.388°	0.371°	0.139*	0.59

White Only	1.177	0.493	1.183	1.496	0.362*	0.477	0.314*	0.541	0.986	1.023	0.961
Asian	0.996	0.243°	1.122	0.494	0.475	0.622	0.351	0.223*	0.728	1.138	1.109
Black	0.661	0.331	0.555	0.952	0.237*	0.319	0.179*	0.472	0.302°	1.466	0.483
Bachelor's Degree or More	1.397	1.131	0.798	0.503	1.305	1.131	1.152	1.487	1.296	0.89	0.578
Unemployed/Other	0.992	1.34	1.455	4.172**	2.759**	1.589	1.734	1.58	3.124**	1.321	3.452**
Essential Worker	0.824	2.522**	0.782	1.143	1.497	1.098	0.969	1.221	2.498**	0.814	2.102*
Job changes during COVID-19	1.241	1.555	1.027	1.148	1.248	1.301	1.071	1.483	1.215	1.453	0.911
Change in Pay/Hours COVID-19	1.004	1.912°	1.497	1.956	1.817°	2.758**	1.431	0.98	1.36	1.248	1.829
Household Income < $50,000	1.042	1.002	0.592	2.773*	1.143	0.540°	1.206	0.832	0.921	0.682	1.003
Homeowner	0.68	0.986	0.814	2.533*	0.783	1.251	1.508	1.485	0.657	2.004	0.965
Family Structure											
Live w/ Spouse	1.201	0.769	0.414**	0.448°	0.838	0.449*	0.833	1.093	0.9	0.546	0.74
Lives w/ Child	1.918*	2.399*	1.502	1.306	1.057	1.358	0.771	0.792	1.036	1.229	1.28
Lives w/ Parents	1.547	0.753	0.376°	0.312°	1.582	0.258*	1.053	1.808	1.216	1.339	0.619
Automobile Access											
More Drivers than Vehicles	0.69	1.024	1.209	2.147°	0.719	1.716	1.548	1.915°	1.005	0.448	1.477
No Working Vehicles	0.319°	2.326	0.716	0.588	0.564	1.09	1.41	1.65	0.474	0.666	0.384
Health- and COVID-related conditions											
Very Good or Excellent Health	1.014	0.761	1.023	0.512°	0.901	0.845	0.837	1.247	1.379	0.655	1.395
Disabled	1.199	0.81	1.23	0.91	0.937	1.352	1.024	1.106	0.476	2.186	0.774
Relevant Underlying Conditions	1.242	1.578	1.374	1.939	1.598	1.654	1.15	1.105	0.691	1.119	1.182
COVID-19 Major Threat to Self	0.824	1.228	0.959	0.763	1.745°	1.04	1.63	1.04	1.746°	0.905	0.864
Tested Positive for COVID-19 Before	1.277	0.756	0.725	0.844	0.439**	0.964	0.78	0.919	1.028	0.74	0.664
Summary Statistics											
N	339	339	339	339	339	339	339	339	339	339	339
Pseudo R2	0.048	0.102	0.07	0.209	0.123	0.084	0.103	0.058	0.086	0.111	0.08

A summary of Table 9 is provided below. The results from the logistic regression of desired transit improvements are organized by improvement rather than explanatory variable.

- **Closer Stops:** Few variables are statistically significant in predicting a respondent selects Closer Stops. Fifty percent of respondents selected this improvement. Though, female and gender nonconforming respondents are 44 less likely to select this improvement and respondents aged 60 and older are almost 90 percent less likely to select this improvement.

- **Extended Hours:** Twenty percent of Intake Survey respondents selected this improvement. Essential workers and respondents living with children are over twice as likely to select this improvement. Respondents that experienced a pay change are almost twice as likely to select this improvement. Asian respondents are 76 percent less likely to select this improvement.
- **Faster Service:** This improvement was selected by a third of Intake Survey respondents. There are no statistically significant results positively associated with selecting this option. Respondents living with a spouse, living with parents, and aged 60 and older are 59 to 78 percent less likely to select this option.
- **Lower Fare:** Just 17 percent of Intake Survey respondents selected this improvement but this improvement has the most statistically significant results. Homeowners and low-income respondents are over twice as likely to select this improvement. Unemployed respondents are 4 times as likely to select this option. Respondents living in households with more drivers than vehicles are twice as likely to select this option. Six more variables are negatively correlated with selecting this improvement including female and gender non-conforming, aged 30 to 60, aged 60 and older, living with a spouse, living with parents, and in good health.
- **More Amenities:** Almost 30 percent of Intake Survey respondents selected this improvement. Unemployed respondents are almost three times as likely to select this improvement. Respondents that experience a pay change and to whom COVID is a major threat are 82 percent and 75 percent more likely to select this improvement. Other variables are negatively associated with selecting this improvement including white, black, aged 30 to 60, aged 60 and older, and have tested positive for COVID. These variables have decreasing effect between 50 and 80 percent.
- **More Frequent Service:** Almost 30 percent of Intake Survey respondents selected this improvement. Just one variable is positively associated with selecting this improvement. Respondents that experience a pay change are almost three times as likely to select this improvement.
- **On Time Service:** Twenty percent of Intake Survey respondents selected this improvement. Only 4 sociodemographic variables are statistically significant for predicting whether a respondent selects this option, all negatively correlated. Respondents that are white, black, aged 30 to 60, or aged 60 and older are 50 to 85 percent less likely to select this option.
- **Real Time Information:** Thirty percent of Intake Survey respondents selected this improvement. Just three variables are statistically significant in this improvement regression. Asian respondents and respondents aged 60 and older are 78 and 61 percent less likely to select this improvement. Respondents in a household with more drivers than vehicles are almost twice as likely to select this improvement.
- **Safer:** Thirty percent of Intake Survey respondents selected this improvement. Essential workers are over twice as likely to select this improvement, unemployed respondents are three times as likely. Respondents to whom COVID-19 is a major threat are 75 percent more likely.

Respondents who are black, aged 30 to 60, or aged 60 and older are 50 to 70 less likely to select this improvement.

- **Transit Advantages:** Just 16 percent of Intake Survey respondents selected this improvement. Two variables a significantly correlated with this improvement. Female and gender non-conforming respondents are 44 percent less likely to select this improvement and respondents aged 60 and older are 86 percent less likely to select this improvement.
- **More Comfortable:** Almost 20 percent of Intake Survey respondents selected this improvement. Essential workers are over twice as likely to select this improvement while unemployed respondents are over three times as likely. Female and gender non-conforming respondents are 40 percent less likely to select this improvement.

Table 10 details the odds ratio estimates regarding the likelihood that a respondent will desire a COVID-19 related transit improvement.

Table 10: Odds ratio estimates from logistic regression models for desired COVID-19 related transit improvements. Columns refer to different dependent variables, rows refer to independent variables.

	Ambassador Presence	Contactless Payment	Boarding and Exit Procedures	Increased Cleaning	Limiting Seating	Live Video Surveillance	Mask Requirement	Metro Transit Police Presence	Text Issues
Intercept	0.69	1.603	0.37	2.496	0.378	2.556	1.843	1.102	0.150*
Socio-demographics									
Female and gender nonconforming	1.352	1.303	0.691	1.32	1.498	1.263	1.762*	0.851	1.501
Age 30-60	1.183	0.771	0.58	0.432*	0.922	1.357	0.801	1.445	1.356
Age 60+	0.878	0.521	0.189*	0.367*	1.532	1.389	1.282	1.058	1.1
White Only	0.615	0.597	0.467	0.456°	0.867	0.362*	0.467	0.725	0.914
Asian	0.449	0.602	1.093	0.735	0.732	0.346°	0.623	0.66	1.133
Black	0.685	0.376	0.424	0.372	0.364	0.215*	0.112**	0.488	0.528
Bachelor's Degree or More	0.793	1.108	0.516°	1.056	2.104*	0.904	1.531	0.937	1.199
Unemployed/Other	1.388	1.584	2.197°	2.470**	1.342	1.282	1.114	1.639	3.474***
Essential Worker	1.185	0.844	1.24	1.447	1.323	1.284	1.009	1.640°	1.401
Job changes during COVID-19	1.142	1.121	1.078	0.866	1.24	0.778	1.262	0.823	1.258
Change in Pay/Hours COVID-19	1.253	1.13	0.909	1.066	0.831	1.098	1.091	0.958	1.214
Household Income < $50,000	0.686	0.553°	1.335	1.746°	1.718°	0.85	1.211	0.64	1.04
Homeowner	0.675	0.858	3.775**	1.13	1.19	0.704	0.756	1.174	0.891
Family Structure									

Live w/ Spouse	0.864	1.028	0.445*	0.601	0.709	0.65	0.762	0.521*	0.908
Lives w/ Child	0.777	1.797*	1.579	1.457	1.572	1.104	0.994	0.704	1.374
Lives w/ Parents	0.437	1.675	0.633	0.398°	0.906	0.756	1.338	0.223*	1.396
Automobile Access									
More Drivers than Vehicles	0.678	1.03	2.616**	1.029	1.877°	0.892	1.185	0.879	1.374
No Working Vehicles	1.484	1.253	0.499	0.648	0.505	0.664	0.503	1.736	0.808
Health- and COVID-related conditions									
Very Good or Excellent Health	1.512	0.783	1.637	1.022	0.881	0.658°	1.194	1.04	1.105
Disabled	0.805	1.068	1.263	0.848	0.97	0.75	1.547	0.977	0.759
Relevant Underlying Conditions	1.245	1.02	1.387	1.880*	1.593	0.935	1.042	0.98	1.298
COVID-19 Major Threat to Self	1.192	1.01	0.925	0.963	1.672°	1.27	1.485	2.044*	1.324
Tested Positive for COVID-19 Before	1.015	0.712	1.046	0.969	0.644°	1.029	0.636°	0.68	0.620°
Summary Statistics									
N	339	339	339	339	339	339	339	339	339
Pseudo R2	0.041	0.049	0.117	0.076	0.08	0.045	0.08	0.065	0.066

A summary of Table 10 is provided below. The results from the logistic regression are organized by improvement rather than explanatory variable.

- **Ambassador Presence:** Thirty percent of Intake Survey respondents selected this improvement. The logistic regression of the COVID-19 measure did not generate any statistically significant results.
- **Contactless Payment:** Almost half of Intake Survey respondents selected this improvement. Low-income respondents are 45 percent less likely to select this measure while respondents living with children are 80 percent more likely.
- **Boarding and Exit Procedures:** Just over 20 percent Intake Survey respondents selected this improvement. Homeowners are almost 4 times as likely to select this measure. Unemployed respondents and respondents in households with more drivers than vehicles are over twice as likely to select this measure. Respondents aged 60 and older, who have a bachelor’s degree or more, and live with a spouse are 50 to 80 percent less likely to select this measure.
- **Increased Cleaning:** Over 50 percent of Intake Survey respondents selected this improvement. Unemployed respondents are over twice as likely to select this measure. Low-income respondents and respondents with a relevant underlying health condition are 75 percent and 88 percent more likely to select this measure. Respondents that are white, aged 30 to 60, aged 60 and older, or live with parents are about 55 to 65 percent less likely to select this measure.
- **Limited Seating:** Just over 50 percent of Intake Survey respondents selected this improvement. All statistically significant results are positively associated with selecting this measure.

Respondents with a bachelor's degree or more are over twice as likely to select this measure. Low-income respondents, respondents in households with more drivers than vehicles, and respondents to whom COVID-19 is a major threat are 60 to 90 percent more likely to select this measure.

- **Live Video Surveillance:** Forty percent of Intake Survey respondents selected this improvement. All statistically significant results are negatively associated with this measure. White, black, and Asian respondents are 65 to 80 percent less likely to select this option; respondents with good health are 34 percent less likely.
- **Mask Requirement:** Over 50 percent of Intake Survey respondents selected this improvement. Female and gender non-conforming respondents are 76 percent more likely to select this measure; black respondents are 89 percent less likely. Respondents that tested positive for COVID-19 are 36 percent less likely to select this measure.
- **Metro Transit Police Presence:** Thirty-nine percent of Intake Survey respondents selected this improvement. Essential workers are 64 percent more likely to select this measure; respondents to whom COVID-19 is a major threat are over twice as likely. Respondents living with a spouse or parents are 48 percent and 78 percent less likely to select this measure, respectively.
- **Text Issues:** Thirty-one percent of Intake Survey respondents selected this improvement. Unemployed respondents are over three times as likely to select this measure. Respondents that tested positive for COVID-19 are 38 percent less likely.

Table 11 details the odds ratio estimate regarding the likelihood that a respondent was or is comfortable using transit or interested in using transit more.

Table 11: Odds ratio estimates from logistic regression models for interest and comfort using public transportation. Columns refer to different dependent variables, rows refer to independent variables.

	Previous Interest	Current Interest	Previous Comfort	Current Comfort
Intercept	0.411	0.061**	1.617	0.214°
Socio-demographics				
Female and gender nonconforming	1.061	1.042	0.912	0.503*
Age 30-60	0.922	2.31	0.828	1.798
Age 60+	0.742	0.933	0.701	1.06
White Only	0.988	0.821	0.644	1.461
Asian	0.734	0.979	0.628	1.272
Black	0.883	2.283	0.516	3.305
Bachelor's Degree or More	1.162	0.877	1.335	0.426*
Unemployed/Other	0.934	0.515	0.967	1.239
Essential Worker	0.773	1.148	0.926	1.455
Job changes during COVID-19	NA	1.759	NA	1.008

Change in Pay/Hours COVID-19	NA	1.07	NA	1.195
Household Income < $50,000	1.079	0.516	0.835	0.68
Homeowner	1.15	0.604	0.704	1.113
Family Structure				
Live w/ Spouse	0.98	1.231	0.952	0.635
Lives w/ Child	1.153	0.875	1.449	1.018
Lives w/ Parents	0.675	2.136	1.081	0.965
Automobile Access				
More Drivers than Vehicles	1.221	0.282°	1.048	0.347°
No Working Vehicles	2.883°	8.692**	1.995	2.81
Health- and COVID-related conditions				
Very Good or Excellent Health	1.22	1.491	1.048	1.576
Disabled	1.138	0.832	1.995	0.330°
Relevant Underlying Conditions	0.557°	1.626	1.258	1.302
COVID-19 Major Threat to Self	NA	1.223	NA	0.614
Tested Positive for COVID-19 Before	NA	1.482	NA	1.369
Summary Statistics				
N	339	339	339	339
Pseudo R2	0.035	0.107	0.022	0.12

A summary of Table 11 is provided below.

- The regression regarding previous comfort with public transit did not generate any statistically significant results.
- Sociodemographic variables were only significant in the regression determining current comfort with transit. Female and gender nonconforming respondents and respondents with a bachelor's degree or more are 50 to 60 percent less likely to indicate comfort with public transit at the time of the survey.
- Family structure variables were not significant in any regression.
- An automobile access variable was significant in each of the three regressions with statistically significant results. Respondents without access to a working vehicle almost 3 times as likely to be previous interested in using transit more and over 8 times as likely to be currently interested in using transit more at this time of the survey. Respondents with more drivers than vehicles in a household are 65 percent less likely to be comfortable with transit and 72 percent less likely to be interested in using transit more at the time of the survey.
- Health- and COVID-19-related conditions were significant in two instances. A respondent with a disability is 67 percent less likely to be comfortable with transit use at the time of the survey. A respondent with a relevant underlying condition is 44 percent less likely to be interested in using transit more before the COVID-19 pandemic.

CHAPTER 5: STATISTICAL ANALYSES OF DAYNAMICA IN-APP DATA

This chapter focuses on describing the daily activity-trip behavior data as well as the in-app survey data recorded with the Daynamica app by study participants. Overall, a total of 3,141 days of activity-trip behavior data were recorded by 154 participants. Not all days have complete activity-trip behavior data throughout the 24 hours due to recording errors, such as phones running out of battery, abnormal app use causing the app to crash, and weak GPS signal. Table 12 details the statistics regarding the completeness of the data collected. In this report, we define a valid activity-trip day as a day with more than 16 hours of data. The remainder of this chapter focuses on summarizing activity and trip statistics using the data associated with the 2,718 valid activity-trip days.

Table 12: Number of days with complete and partial data, broken down by day of the week (N= 3,141).

Day of the Week	# of days with 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	296 (65.1%)	316 (69.5%)	373 (82.0%)	415 (91.2%)	455
Tuesday	323 (72.4%)	345 (77.4%)	385 (86.3%)	422 (94.6%)	446
Wednesday	320 (71.4%)	343 (76.6%)	392 (87.5%)	428 (95.5%)	448
Thursday	318 (69.7%)	345 (76.3%)	387 (84.9%)	438 (96.1%)	456
Friday	325 (70.3%)	347 (75.1%)	400 (86.6%)	444 (96.1%)	462
Saturday	317 (71.2%)	337 (75.7 %)	395 (88.8%)	433 (97.3%)	445
Sunday	322 (75.1%)	345 (80.4%)	386 (90.0%)	419 (97.7%)	429
Total	2,221 (70.7%)	2,378 (75.7%)	2,718 (86.5%)	2,999 (95.5%)	3,141

5.1 DAY EPISODE STATISTICS

This section details the activity-trip behavior data summarized by day, including results from the end of day surveys pushed to participants once per day. Table 13 below contains the averages of activity and trip characteristics.

Table 13: Day level summary statistics (N = 2,718 Days)

Average	Mean	SD	Min	Max
Recorded Data per Day (Minutes)	1,407.63	92.82	961	1,440
Total Activity Duration per Day (Minutes)	1,327.34	134.24	157.48	1,440
Total Trip Duration per Day (Minutes)	80.29	93.22	0	1,282.5
Total Trip Distance per Day (Miles)	31.43	49.10	0	559.97
Activity Count per Day	5.38	3.74	1	56
Trip Count per Day	4.08	3.49	0	51

5.1.1 Activities per Day Summary

Table 14 provides activity frequency and duration averages, per person per day, aggregated by activity type. The averages are also aggregated by day of week, comparing weekends, weekdays, and all days. Figure 9 below Table 14 presents the same information as a cumulative visual composition. The next section provides more detail about activities and activity surveys (Activity Episode Statistics).

Table 14: Numeric values of activity frequency and duration per person per day by activity type.

Activity Type	Number of Activities per Person per Day (%)			Activity Hours per Person per Day (%)		
	Weekend	Weekday	All Activities	Weekend	Weekday	All Activities
Home	2.35 (40.5)	2.38 (45.7)	2.37 (44.1)	17.34 (79.2)	16.83 (75.8)	16.98 (76.7)
Work	0.24 (4.1)	0.63 (12.1)	0.52 (9.6)	0.85 (3.9)	2.72 (12.2)	2.18 (9.9)
Education	0.04 (0.7)	0.13 (2.5)	0.1 (1.9)	0.22 (1)	0.26 (1.2)	0.25 (1.1)
Shop	0.77 (13.3)	0.49 (9.3)	0.57 (10.6)	0.35 (1.6)	0.21 (1)	0.25 (1.1)
Eat Out	0.27 (4.6)	0.22 (4.3)	0.24 (4.4)	0.24 (1.1)	0.15 (0.7)	0.17 (0.8)
Personal Business	0.28 (4.8)	0.31 (5.9)	0.3 (5.6)	0.41 (1.9)	0.31 (1.4)	0.34 (1.5)
Leisure & Rec'n	0.95 (16.4)	0.5 (9.6)	0.63 (11.7)	1.32 (6)	0.79 (3.6)	0.94 (4.3)
Other	0.9 (15.5)	0.55 (10.6)	0.65 (12.1)	1.18 (5.4)	0.93 (4.2)	1.01 (4.6)
Total	5.79 (100)	5.21 (100)	5.38 (100)	21.9 (100)	22.21 (100)	22.12 (100)

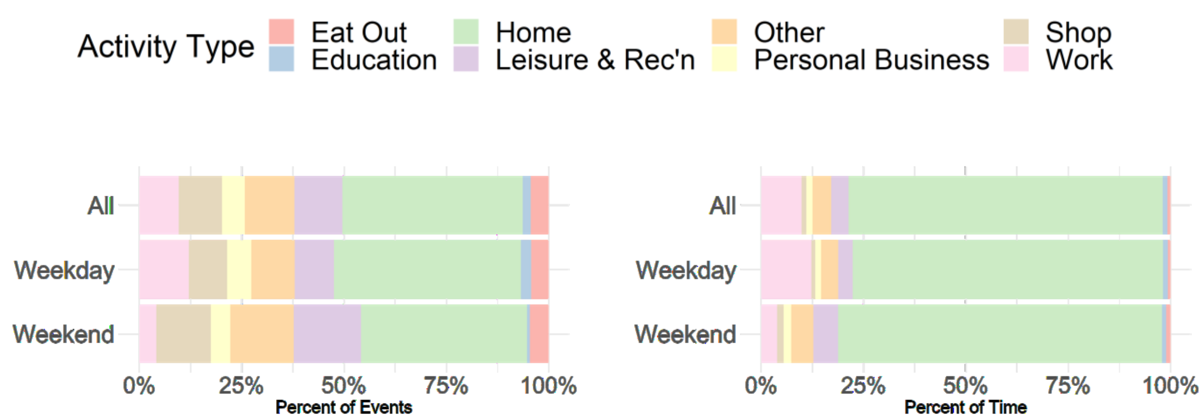


Figure 9: Visual composition of activity frequency and duration per person per day by activity type, illustrated as percent of day

5.1.2 Trips per Day Summary

Table 15 provides trip frequency, duration, and distance averages, per person per day, aggregated by primary trip mode. The primary trip mode is the mode used the most (by distance) during a trip. A trip can be comprised of a single segment with a single mode or of multiple segments with multiple modes.

For example, many car trips contain just one segment of car use while some others could be comprised of one car segment and one or two walking segments. The averages in Table 15 are aggregated by day of week, comparing weekends, weekdays, and all days. Figure 10 below Table 15 presents the same information as a cumulative visual composition.

Table 15: Numeric values of trip frequency, duration, and distance per person per day by primary trip mode.

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 (%)**		
	Weekend	Weekday	All Trips	Weekend	Weekday	All Trips	Weekend	Weekday	All Trips
Bike	0.05 (1)	0.04 (1)	0.04 (1)	1.12 (1.3)	0.96 (1.3)	1 (1.3)	0.19 (0.5)	0.14 (0.5)	0.15 (0.5)
Bus	0.03 (0.7)	0.04 (1.1)	0.04 (1)	0.79 (0.9)	1.27 (1.8)	1.13 (1.5)	0.22 (0.6)	0.33 (1.2)	0.3 (0.9)
Car	3.43 (75.6)	3.06 (79.1)	3.17 (78)	68.78 (78.4)	56.18 (79)	59.8 (78.8)	37.76 (95.9)	27.08 (95.3)	30.15 (95.5)
Other	0.09 (2)	0.05 (1.2)	0.06 (1.5)	0.89 (1)	0.75 (1.1)	0.79 (1)	0.19 (0.5)	0.18 (0.6)	0.18 (0.6)
Rail	0.01 (0.2)	0 (0.1)	0 (0.1)	0.16 (0.2)	0.03 (0)	0.07 (0.1)	0.02 (0.1)	0 (0)	0.01 (0)
Walk	0.93 (20.5)	0.67 (17.4)	0.75 (18.4)	15.94 (18.2)	11.92 (16.8)	13.08 (17.2)	0.99 (2.5)	0.69 (2.4)	0.78 (2.5)
All	4.54 (100)	3.86 (100)	4.06 (100)	87.68 (100)	71.11 (100)	75.87 (100)	39.36 (100)	28.43 (100)	31.57 (100)

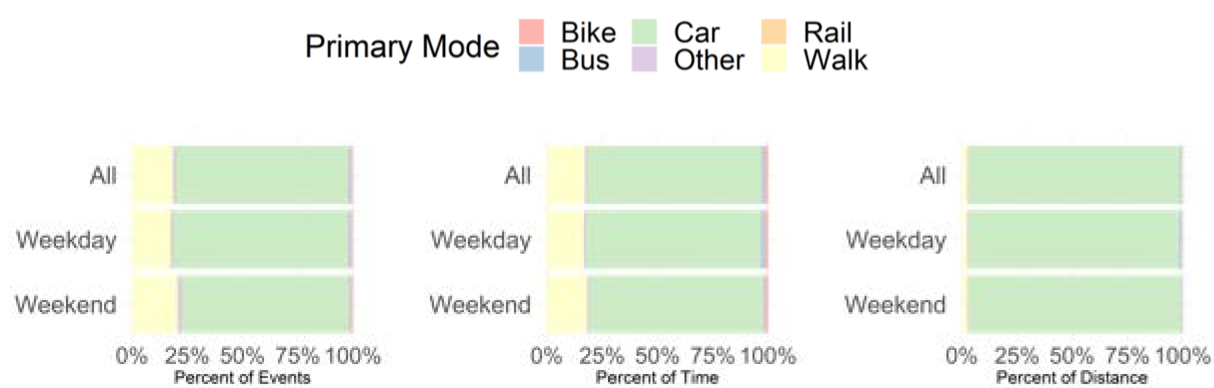


Figure 10: Visual composition of trip frequency, duration, and distance per person per day by the primary trip mode, illustrated as percent of the day.

Table 16 presents descriptive statistics for the trip segment data recorded by study participants. Frequencies are tabulated by number of trips, travel duration in minutes, and travel distance in miles.

They are also aggregated by day of week, comparing weekends, weekdays, and all days. Figure 11 below Table 16 presents the same information as a cumulative visual composition.

Table 16: Numeric values of trip segment frequency, duration, and distance per person per day by segment mode.

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 (%)		
	Weekend	Weekday	All Trips	Weekend	Weekday	All Trips	Weekend	Weekday	All Trips
Bike	0.06 (1.2)	0.05 (1.2)	0.05 (1.2)	1.18 (1.3)	0.9 (1.2)	0.98 (1.2)	0.19 (0.5)	0.14 (0.5)	0.15 (0.5)
Bus	0.03 (0.7)	0.05 (1.1)	0.04 (1)	1.56 (1.7)	2.33 (3.1)	2.11 (2.6)	0.21 (0.5)	0.33 (1.1)	0.29 (0.9)
Car	3.52 (72.3)	3.13 (75.2)	3.24 (74.2)	68.03 (74.3)	55.89 (73.8)	59.38 (74)	37.69 (95.7)	27.02 (95)	30.08 (95.3)
Other	0.11 (2.2)	0.06 (1.5)	0.08 (1.8)	2.82 (3.1)	2.52 (3.3)	2.6 (3.2)	0.19 (0.5)	0.18 (0.6)	0.18 (0.6)
Rail	0.01 (0.2)	0 (0.1)	0.01 (0.1)	0.17 (0.2)	0.57 (0.7)	0.45 (0.6)	0.03 (0.1)	0 (0)	0.01 (0)
Walk	1.14 (23.4)	0.87 (20.8)	0.95 (21.7)	17.76 (19.4)	13.54 (17.9)	14.75 (18.4)	1.05 (2.7)	0.77 (2.7)	0.85 (2.7)
All	4.87 (100)	4.16 (100)	4.36 (100)	91.52 (100)	75.74 (100)	80.28 (100)	39.37 (100)	28.44 (100)	31.58 (100)

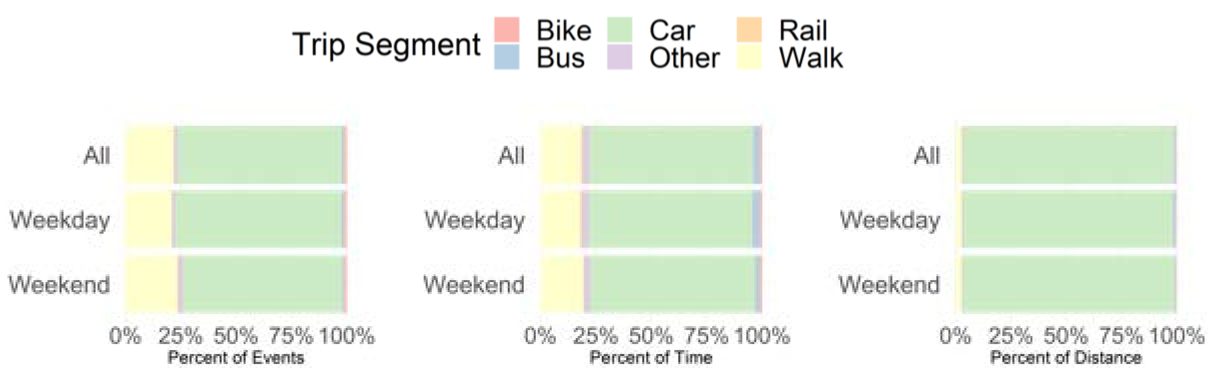


Figure 11: Visual composition of trip segment frequency, duration, and distance per person per day by the segment mode, illustrated as percent of the day.

Table 17 provides trip frequency, duration, and distance averages, per person per day, aggregated by trip purpose. Trip purpose is defined as the activity type immediately following the end of the trip. The averages are aggregated by day of week, comparing weekends, weekdays, and all days. Figure 12 below Table 17 presents the same information as a cumulative visual composition.

Table 17: Numeric values of trip frequency, duration, and distance per person per day by trip purpose.

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 (%)		
	Weekend	Weekday	All Trips	Weekend	Weekday	All Trips	Weekend	Weekday	All Trips
Home	1.62 (35.6)	1.51 (38.9)	1.55 (37.9)	33.88 (37)	28.92 (38.2)	30.34 (37.8)	13.91 (35.3)	10.08 (35.5)	11.18 (35.4)
Work	0.2 (4.5)	0.56 (14.3)	0.46 (11.2)	5.03 (5.5)	12.32 (16.3)	10.23 (12.7)	1.59 (4.1)	4.52 (15.9)	3.68 (11.7)
Education	0.03 (0.6)	0.11 (2.7)	0.08 (2)	0.29 (0.3)	1.39 (1.8)	1.08 (1.3)	0.12 (0.3)	0.58 (2)	0.45 (1.4)
Shop	0.67 (14.6)	0.42 (10.7)	0.49 (11.9)	11.37 (12.4)	6.64 (8.8)	8 (10)	4.96 (12.6)	2.79 (9.8)	3.41 (10.8)
Eat Out	0.24 (5.2)	0.17 (4.5)	0.19 (4.7)	5.05 (5.5)	3.27 (4.3)	3.78 (4.7)	1.84 (4.7)	1.26 (4.4)	1.43 (4.5)
Personal Business	0.23 (5.1)	0.25 (6.5)	0.25 (6.1)	5.34 (5.8)	5.62 (7.4)	5.54 (6.9)	2.93 (7.4)	2.32 (8.2)	2.5 (7.9)
Leisure & Rec'n	0.75 (16.4)	0.36 (9.3)	0.47 (11.6)	13.62 (14.9)	6.94 (9.2)	8.86 (11)	6.65 (16.9)	2.3 (8.1)	3.55 (11.2)
Other	0.75 (16.4)	0.46 (11.7)	0.54 (13.2)	14.63 (16)	8.9 (11.7)	10.54 (13.1)	6.46 (16.4)	4.03 (14.2)	4.73 (15)
No Trip Purpose	0.07 (1.6)	0.05 (1.4)	0.06 (1.5)	2.3 (2.5)	1.76 (2.3)	1.91 (2.4)	0.91 (2.3)	0.55 (1.9)	0.65 (2.1)
All	4.56 (100)	3.89 (100)	4.08 (100)	91.52 (100)	75.74 (100)	80.28 (100)	39.36 (100)	28.43 (100)	31.57 (100)

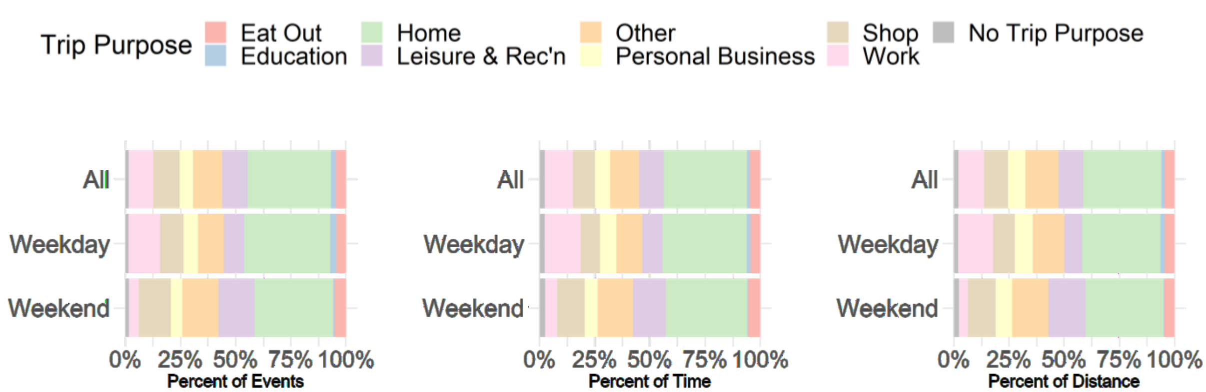


Figure 12: Visual composition of trip frequency, duration, and distance per person per day by trip purpose, illustrated as percent of the day.

5.1.3 End of Day Survey Statistics

Table 18 below details descriptive statistics from the end of day surveys, summarizing 7 questions asked in the survey. An important use of end of day surveys is to measure behaviors not captured by GPS tracking. Though participants recorded 2,718 days with over 16 hours of data, they only completed 2,388 total surveys. The first two questions ask if any activities were cancelled for COVID-19 related reasons, and if so, what types and for what reasons. The next question asks whether limited transportation options or lack of transportation options prevented the participant from engaging in any activities, and if so, what types. The fourth question asks if participants are concerned they contracted COVID-19 that day. The fifth questions asks if a participant worked from home that day and for how many hours. The last two questions ask about shopping behavior, including what they are buying online and for what things they are using in-store or curbside pick-up services.

Table 18: End of day survey summary statistics (N = 2,388 Days)

Variable Name	N	Percent
Days with End of Day Survey	2,388	100.00
Days with activities cancelled because of COVID-19 by type		
Total	474	17.44
Work	91	3.35
Shop	141	5.90
Personal Business	81	3.39
Eat Out	234	9.80
Leisure and Recreation	208	8.71
Education	21	0.88
Other	36	1.51
Reason for cancelled activity		
Activity no longer possible	153	6.41
Did not want extra risk	381	15.95
New obligations	53	2.22
Other Reasons	36	1.51
Transportation barriers preventing activity by type		
Total days	48	2.01
Shopping	25	1.05
Eat out	14	0.59
Personal business	12	0.50
Leisure and recreation	22	0.92
Work	11	0.46
Education	6	0.25
Other	4	0.28
Days concerned with having contracted COVID-19		
Strongly agree	114	4.78
Agree	200	8.38
Unsure	225	9.43

Disagree	753	31.55
Strongly disagree	1,095	45.87
Days worked from home by duration		
Total days	865	36.24
0-1 Hours	27	1.12
1 – 4 Hours	205	8.58
4 – 8 Hours	246	10.30
8+ Hours	387	16.21
Days shopped online by type of goods		
Total days	512	21.45
Clothing	108	4.52
Groceries	88	3.69
Household Supplies	119	4.98
Non-Essential Items	236	9.88
Other Essential Items	96	4.02
Prepared Food	50	2.09
Days used In-store/curbside pickup by type of goods		
Total days	335	14.03
Clothing	80	3.35
Groceries	58	2.43
Household Supplies	76	3.18
Non-Essential Items	190	7.96
Other Essential Items	97	4.06
Prepared Food	53	2.22

Figure 13 below expands on the work from home statistics presented in Table 18, disaggregated by day of the week.

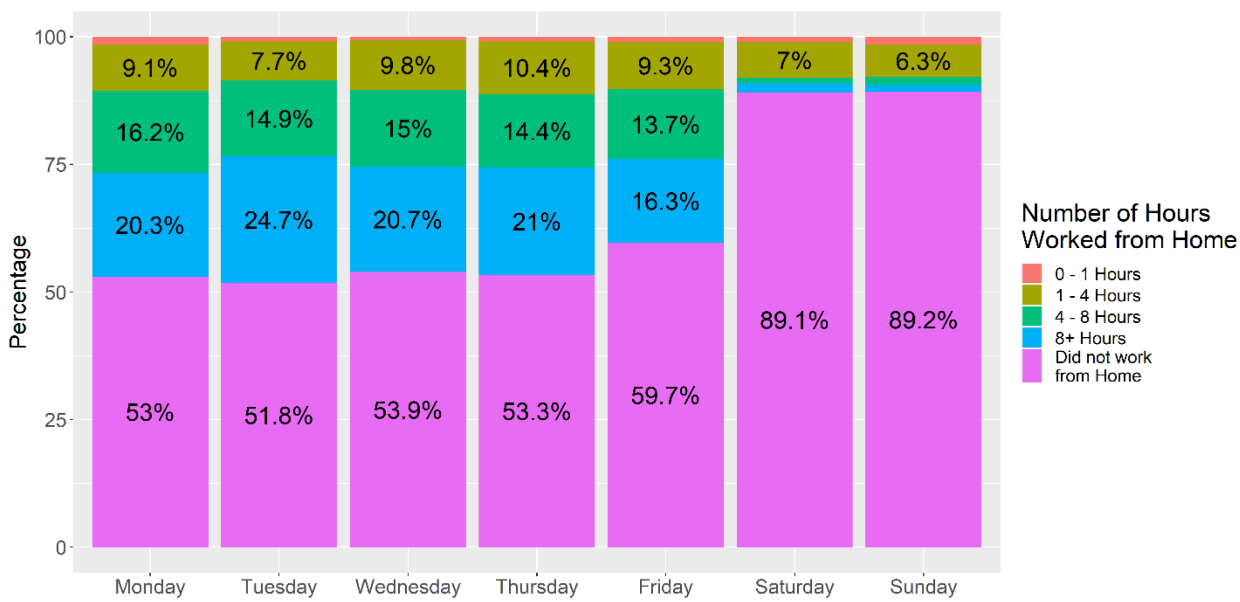


Figure 13: Work from home duration stratified by day of week

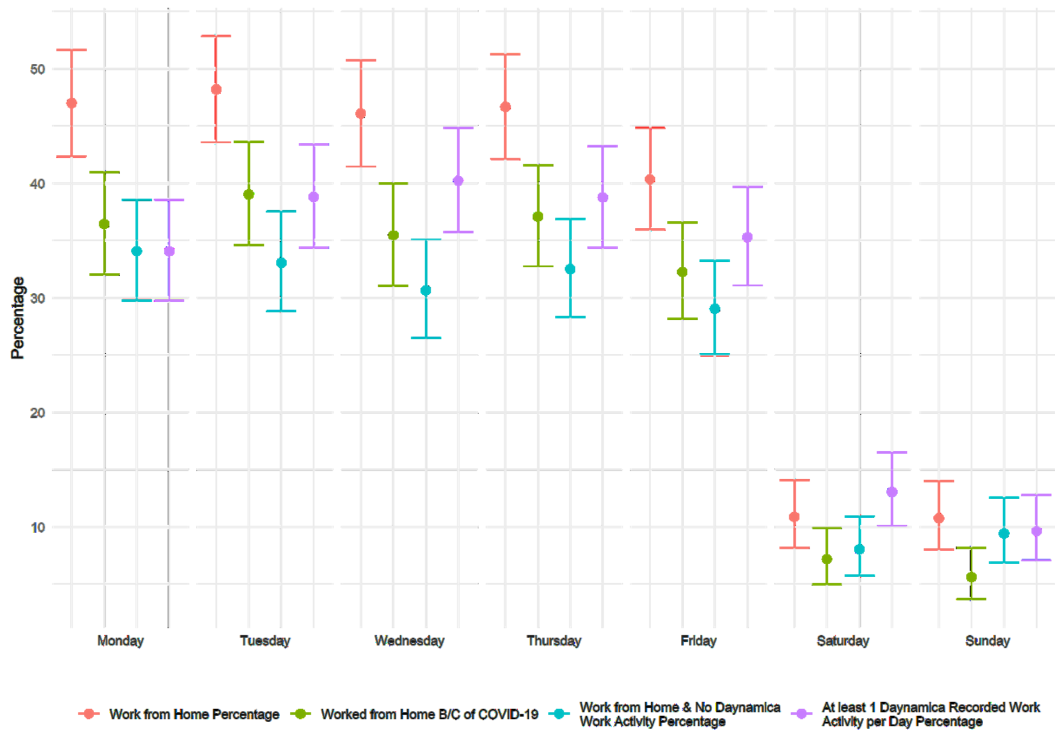


Figure 14: Work from home and related metrics relative probabilities stratified by day of week

Figure 14 above shows the relative percentages of various types of workdays occurring, stratified by day of the week. Standard binomial confidence intervals are computed. Within each day the leftmost point (Red) refers to the percent of the time that and individual indicated that they worked from home in the end of day survey, regardless of the reason. We can see that the rate of working from home is consistent for the first four weekdays and the percentage drops for Fridays. The overall rate is significantly lower on the weekend days. The next point (Green) refers to work form home days in which the individual indicated that the reason for working from home was because of COVID-19. This is a special case of working from home, meaning that it will be less than the working from home percentage.

The third point for each day (Blue) refers to when individuals indicated that they worked from home in the End of Day survey and we did not detect any Work activities for that day. This is also a subset of the work from home days. The final point refers to the percentage of days in which we recorded at least 1 work activity for an individual. No requirement was made for the end of day survey.

Overall, there are similar trends across all of the points each day of the week; the relative positions among the points does not change dramatically with the day of the week.

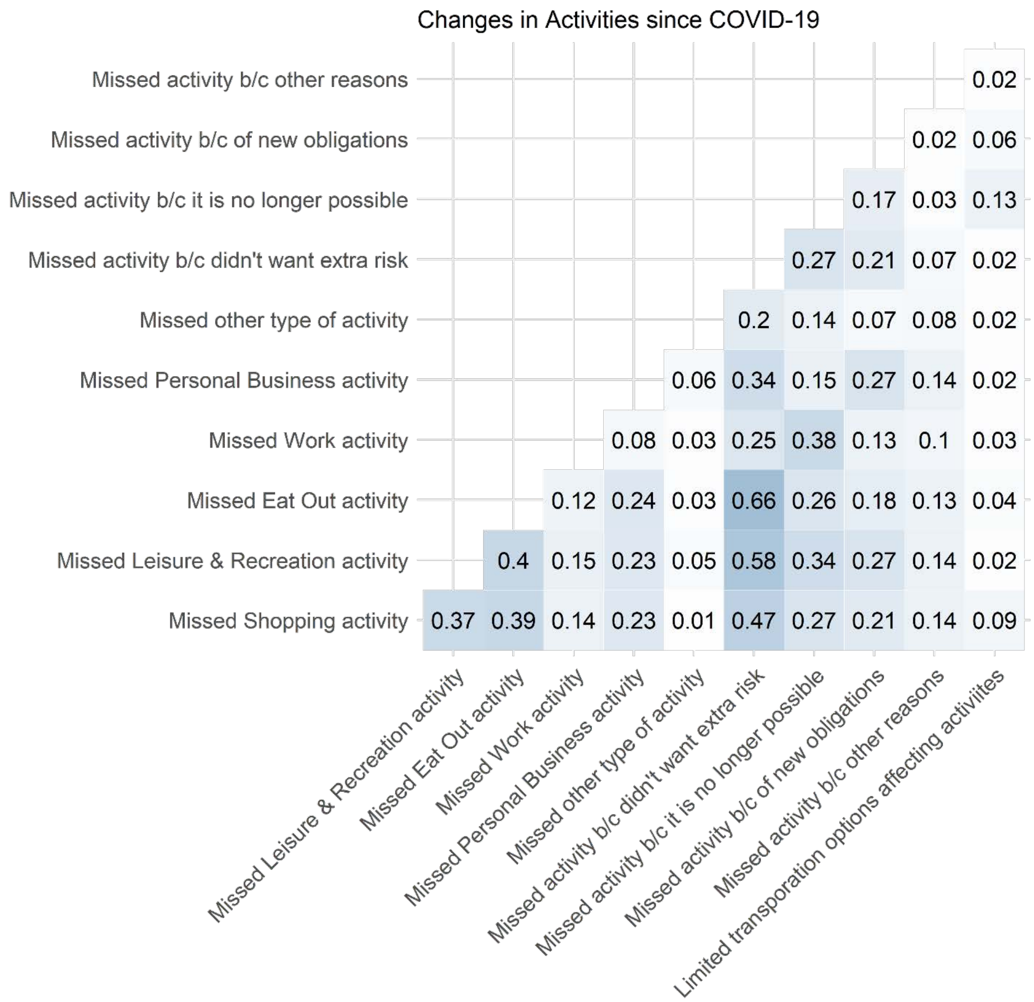


Figure 15: Missed activities and reasons why correlation plot

Figure 15 highlights the specific activities that individuals indicated they missed out on because of COVID-19 as well as the reasons why. While the tabulations in Table 18 above highlight the marginal rates of responses, this plot focuses on the interaction between the various responses. The plot is laid out in a grid where the colors and numbers represent the Pearson's correlation between these data points. A higher correlation indicates that the answers were more frequently selected together.

Key findings form this plot show that often the reason for missing Eating Out activities was because of concern over COVID-19 and not because of reasons like new obligations or limited transportation options.

5.1.4 Regression Model – Day Episodes

Table 19 presents the odds ratio estimates from the logistic regression of five dependent variables from the end of day survey, described in Table 18: the participant's concern with contracting COVID-19 that day; frequency of transportation barriers; frequency of working from home; frequency of online shopping; and frequency of in-store/curbside pick-up.

Few of the independent variables across the five models have statistically significant associations. An increase in the total number of trips taken increases the likelihood of concern with contracting COVID-19 and the chance of in-store or curbside pick-up that day but it decreases the likelihood of the participant working from home or shopping online that day.

Essential workers and unemployed respondents are much less likely to work from home. Participants are also much less likely to work from home on the weekend.

Participants to whom COVID-19 is a major threat are much more likely to be concerned with COVID-19 or to encounter transportation barriers that day.

Lastly, participants without a working vehicle at home are less likely to have shopped online that day. Plus, as the total time at home increases, the chance of the participant shopping online that day decreases.

Table 19: Odds ratio estimates from five logistic regression models for End of Day Survey results. The value transformations for the five dependent variables are: for Concerned with COVID-19, 1 equals a participant selected "agree" or "strongly agree;" for the remaining 4 dependent variables, 1 equals a participant selected "yes."

	Concerned with COVID-19	**Transportation Barrier**	**Work from Home**	**Online Shopping**	**In-store pickup/curbside pickup**
Intercept	0.034	0.007	0.153	1.246	0.081
Day Level Data					
Weekend	0.912	1.651	0.025***	0.885	0.976
Total Time at Home (hours)	1.036	0.946	1.038	0.938°	0.989
Total Trips	1.140***	1.019	0.878***	0.968°	1.160***
Socio-demographics					
Female and gender nonconforming	1.234	0.368	3.462	1.049	0.959
Age 30-60	0.973	0.473	1.585	1.303	0.857
Age 60+	0.399	0	0.408	1.278	0.975
White	0.511	4.007	0.569	0.438	0.585
Asian	3.015	7.351	1.203	0.587	0.454
Black	8.723	12.822	49.033	0.583	0.074
Bachelor's Degree or More	0.403	1.291	1.885	1.064	0.79
Unemployed/Other	0.488	1.502	0.011*	1.449	0.892
Essential Worker	1.186	3.393	0.053°	1.659	1.862

Job changes during COVID-19	0.737	0.976	0.596	1.252	0.876
Change in Pay/Hours COVID-19	3.562	1.102	9.131	0.813	1.357
Household Income > $50,000	1.062	0.303	0.3	0.983	2.061
Homeowner	0.734	3.134	3.865	1.215	1.024
Family Structure					
Live w/ Spouse	0.711	0.268	3.897	0.804	0.557
Lives w/ Child	1.063	1.374	0.664	1.214	1.379
Lives w/ Parents	3.871	1.414	1.509	0.261	1.151
Automobile Access					
More Drivers than Vehicles	0.641	2.67	1.791	1.062	1.289
No Working Vehicles	1.621	2.55	2.174	0.311°	0.261
Health- and COVID-19-related conditions					
Very Good or Excellent Health	0.62	0.632	0.98	0.923	0.979
Disabled	0.887	0.912	0.391	2.098	2.033
Relevant Underlying Conditions	1.418	0.809	1.321	0.835	0.829
COVID-19 Major Threat to Self	5.565°	10.372**	0.4	1.446	1.245
Tested Positive for COVID-19 Before	1.111	1.819	2.568	1.328	1.117
Summary Stats					
R Squared	0.41	0.296	0.678	0.184	0.257
N	2,388	2,387	2,387	2,387	2,387

5.2 ACTIVITY EPISODE STATISTICS

Figure 16 below shows the density of activities in the 7-county Twin Cities Metro Area from the 154 study participants that completed Daynamica data collection. The activity density factors in the duration of a particular activity. The most prominent activity types are Home and Work.

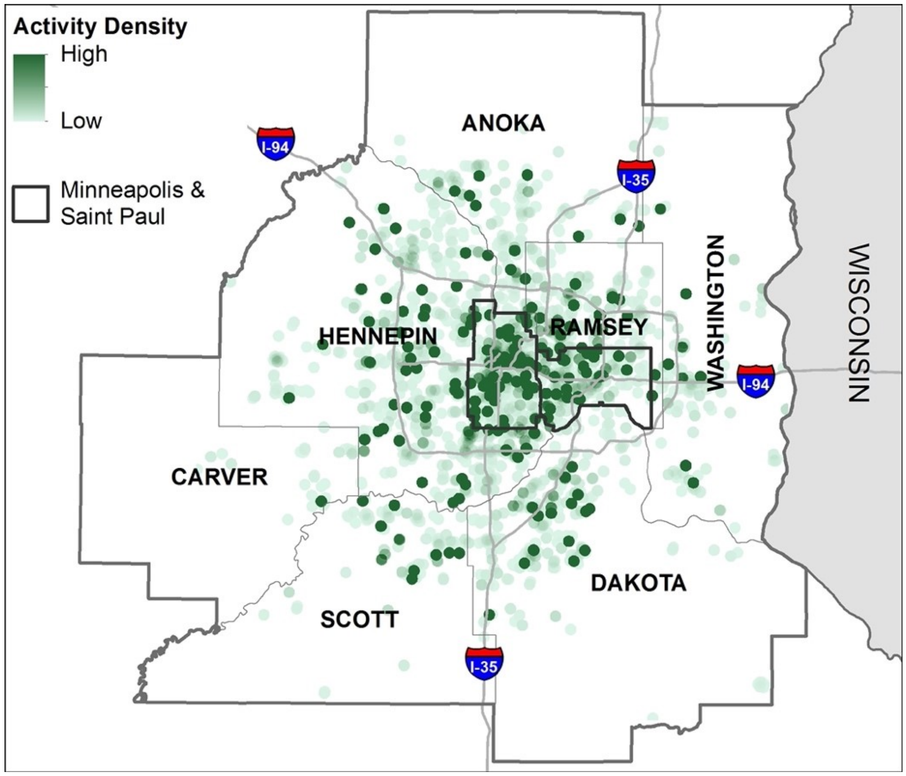


Figure 16: Activity density distribution of Daynamica participants (N = 154)

Table 20 summarizes several averages describing the activity episodes recorded. Duration per Activity summarizes all recorded activities (N = 14,625). The remaining descriptive statistics in Table 20 summarize activities with completed episode surveys (N = 11,761). Close Contacts are defined as individuals the participant regularly interacts with in person.

Table 21 summarizes the total number of activities recorded, categorized by activity type. The table compares all recorded activities to all activities with a completed episode survey. Participants specify the activity type before taking the episode survey; Daynamica is also able to predict the activity type without participant input if it is a revisited location that the participant has previously labeled.

Table 20: Activity summary statistics

Variable Name	N	Mean	SD	Min	Max
Duration per Activity (minutes)	14,625	246.68	312.82	0.5	1,440
Contacts per Activity	11,761	2.32	4.64	0	25
Contacts per Hour during Activities	11,761	10.01	50.99	0	1,800
Close Contacts per Activity	11,761	1.23	2.87	0	25
Close Contacts per Hour during Activities	11,761	3.69	22.51	0	1,500

Table 21: Activity summary statistics by activity type

	Daynamica Data		Daynamica Data with Episode Survey	
Variable Name	N	Percent	N	Percent
Activity Type	14,625	100	11,761	100
Home	6,446	44.08	5,466	46.48
Work	1,407	9.62	1,284	10.92
Education	284	1.94	217	1.85
Shop	1,546	10.57	1,460	12.41
Personal Business	815	5.57	758	6.45
Eat Out	643	4.4	623	5.30
Leisure and Recreation	1,713	11.71	1,437	12.22
Other	1,771	12.11	516	4.39

5.2.1 Activity Survey Statistics

Table 22 below summarizes descriptive statistics of five questions from the activity surveys. The activity environment question asks how crowded an activity was at its peak. Concerned with COVID-19 during activity asks the participant how much they agree with this statement: I am concerned with my risk of contracting coronavirus. Activity importance asks how important the participant considers the activity. Activity timeliness asks about the time sensitivity of the activity. Shopping activity purpose asks about the goods category that bests describe the purpose of the shopping trip. The activity importance and timeliness questions were only asked for Non-Home and Non-Work activities.

Table 22: Activity survey summary statistics (N = 11,761)

Variable Name	N	Percent
Activity Environment		
Not Crowded	9,247	78.68
Somewhat Crowded	1,845	15.70
Crowded	491	4.18
Very Crowded	169	1.44
Concerned with COVID-19 During Activity		
Strongly disagree	7,369	62.66
Disagree	3,071	26.11
Undecided	740	6.29
Agree	477	4.06
Strongly agree	104	0.88
Non-home Non-Work Activity with Episode Survey	5,011	42.60
Activity Importance		
Not at all Important	857	14.90
Slightly Important	1,421	24.71
Important	1,775	30.87
Very Important	1,647	28.64

Unsure	50	0.87
Activity Timeliness: Had to be done…		
At this time	2,102	36.56
Around this time	1,411	24.54
Today	819	14.24
This week	336	5.84
This month	75	1.30
Not time sensitive	1,007	17.51
Shopping Activity Purpose: Non-Exclusive		
Clothing	112	7.67
Groceries	626	42.88
Household Supplies	221	15.14
Non-Essential Items	327	22.40
Other Essential Items	348	23.84
Takeout Food	144	9.86

5.2.2 Activity Importance Summary

Here, we expand on the activity importance statistics presented in Table 22. Figure 17 illustrates the distribution of activity importance for different types of activities. The figure illustrates that Eat Out is generally considered the least important while Personal Business is generally considered the most important.

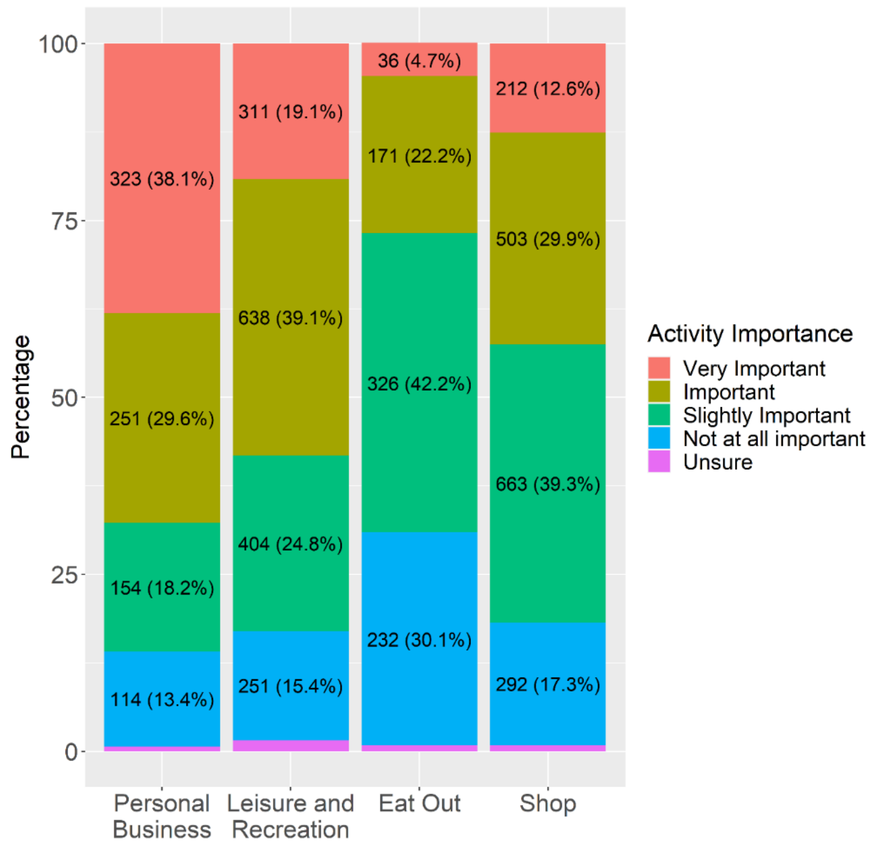


Figure 17: Activity importance frequency by activity types

Figure 18 on the next page illustrates the common reasons for why an activity was important. Results only consider activities that were marked “slightly important,” “important,” or “very important.” Options were not exclusive; participants could select multiple reasons. Participants most commonly selected Groceries and Shopping for the reason why a shopping trip was important. Personal was a common choice for Personal Business activities. Leisure and recreation had the widest spread of different reasons; the top four reasons are Social, Familial, Health, and Personal.

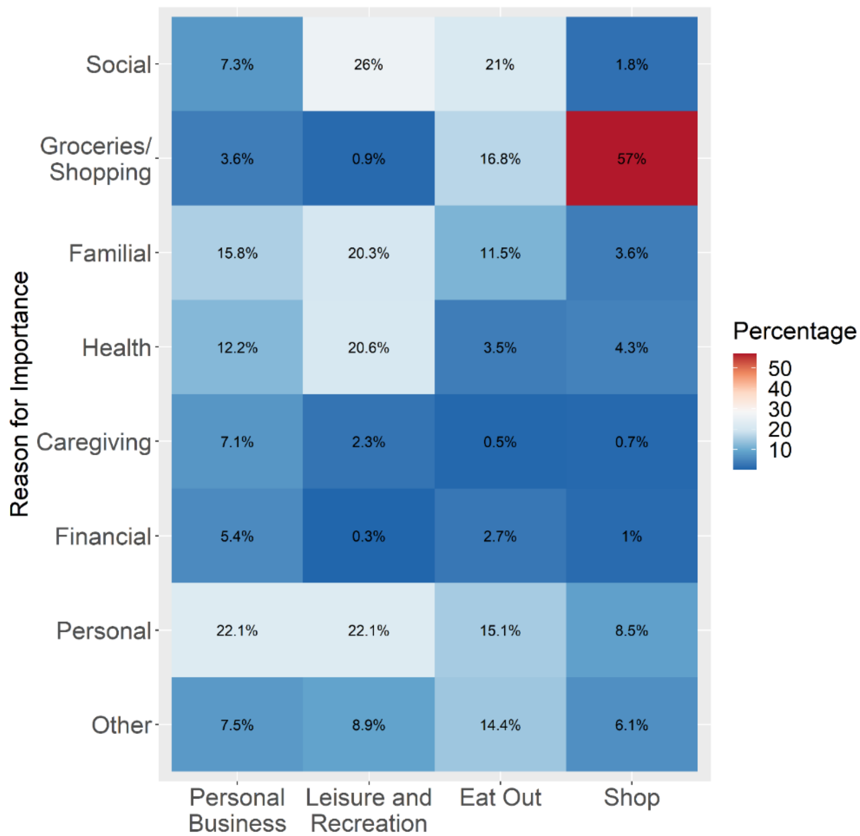


Figure 18: Frequency of reasons why participants label activities as important.

5.2.3 Regression Model — Activity Episodes

Table 23 presents the odds ratio estimates from the logistic regression of four dependent variables from the activity survey: the participant's amount of concern with contracting COVID-19 during the activity; the importance of the activity; and the time sensitivity of the activity. Concern with COVID-19 is presented twice, once among all activities and once among Out-and-About activities (Shop, Eat Out, Personal Business, and Leisure & Recreation activities). The remaining two regressions are also restricted to Out-and-About activities.

Concern with COVID-19 is more likely as the number of contacts increases. The effect size of the association is the same across the two sample populations (all activities vs. Out-and-About activities). There is a slight negative association with activity importance as the number of contacts increases.

Respondents are less likely to be concerned with COVID-19 as the number of close contacts (e.g., friends and family) increases during Out-and-About activities; though, respondents are also more likely to consider the Out-and-About activities timely.

Activity types are compared to the reference category (baseline) Home in the first regression among all activities but to the reference category Shop in the other three regressions among Out-and-About activities. Generally, respondents are much more likely to be concerned with COVID-19 when at an activity other than Home. The odds ratio is greatest for Other activities and lowest for Education activities but these types also have the fewest recorded instances. Respondents are more likely to be concerned with COVID-19 during Personal Business activities and Leisure and Recreation activities among the Out-and-About activities. These activity types are also more likely to be consider time sensitive while Eat Out activities are more likely to be considered important.

There are no significant association with activity start time.

Short and medium distance trips have a negative association with concern with COVID-19. Medium distance trips also have a positive association with activity importance while long distance trips have a positive association with activity timeliness.

Female and gender nonconforming respondents are over 60 percent less likely to consider an activity important. A Black respondent is much more likely to consider an activity important; however, race categories have few other significant associations.

Respondents that experienced a job change are less likely to consider an activity important.

Respondents for whom COVID-19 is a major threat are much more likely to be concerned with COVID-19. No other independent variables have a significant association.

Table 23: Odds ratio estimates for four logistic regression models for activity survey results. The value transformations for the four dependent variables are: for Concerned with COVID-19, 1 equals a participant selected “agree” or “strongly agree;” for Activity Importance, 1 equals a participant selected “important” or “very important;” for Activity Timeliness, 1 equals a participant selected “at this time.” Concern with COVID-19 is presented twice, once among all activities and once among Out-and-About activities (Shop, Eat Out, Personal Business, and Leisure & Recreation activities). The remaining two regressions are also restricted to Out-and-About activities.

	All Activities	Out-and-About Activities		
	Concerned with COVID-19	**Concerned with COVID-19**	**Activity importance**	**Activity timeliness**
Intercept	0.000**	0.018	1.994	0.123
Activity Level Data				
Activity Duration (Minutes)	1	1	0.999*	1
Activity Contacts	1.208***	1.196***	0.952***	1.01
Activity Close Contacts	0.994	0.909*	0.998	1.086**
Activity type				
Work	46.392***	NA	NA	NA
Education	13.413***	NA	NA	NA
Shop	55.769***	Baseline	Baseline	Baseline
Eat Out	52.430***	1.009	2.365***	0.965
Personal Business	39.524***	0.565*	0.819	5.688***
Leisure & Rec'n	39.370***	0.659°	0.902	2.537***

Other	60.358***	29.077	0	0.971
Activity start time				
Morning	1.226	0.961	1.05	1.361
Midday	0.809	0.791	0.886	0.764
Afternoon	0.693	0.785	0.8	0.827
Evening	0.743	0.998	0.745	1.091
Distance to home location				
Short Distance (5-10 Miles)	0.756	0.633°	1.065	1.185
Medium Distance (10-25)	0.514**	0.521*	1.481*	0.928
Long Distance (25+)	1.114	1.443	1.205	1.703***
Weekend	0.865	0.91	1.344**	0.830°
Socio-demographics				
Female and gender nonconforming	3.293	2.379	0.349**	0.82
Age 30-60	1.364	1.17	0.495	2.096
Age 60+	3.611	2.823	0.381	1.222
White	1.262	1.268	1.005	0.301
Asian	1.64	1.323	1.453	0.381
Black	0.068	0.159	18.781°	0.194
Bachelor’s Degree or More	0.537	0.498	1.083	0.964
Unemployed/Other	0.509	0.479	0.505	1.41
Essential Worker	1.136	1.601	0.76	1.116
Job changes during COVID-19	0.931	0.677	0.411*	1.135
Change in Pay/Hours COVID-19	2.628	2.935	0.534	0.8
Household Income > $50,000	0.479	0.501	0.724	1.218
Homeowner	0.618	0.659	1.267	1.367
Family Structure				
Live w/ Spouse	0.858	0.756	0.53	0.97
Lives w/ Child	0.747	0.951	0.655	0.862
Lives w/ Parents	6.325	12.379	0.475	1.986
Automobile Access				
More Drivers than Vehicles	1.052	1.022	1.073	1.205
No Working Vehicles	0.216	0.2	1.585	2.135
Health- and COVID-19-related conditions				

Very Good or Excellent Health	0.973	0.714	0.698	0.981
Disabled	0.334	0.619	0.587	1.59
Relevant Underlying Conditions	1.388	1.145	0.68	0.756
COVID-19 Major Threat to Self	10.239°	7.047°	1.071	1.09
Tested Positive for COVID-19 Before	0.847	0.723	1.096	0.709
Summary Stats				
R Squared	0.556	0.471	0.195	0.343
N	11,485	4,183	4,183	4,183

5.3 TRIP EPISODE STATISTICS

This section describes data recorded from trips episodes and trip surveys. Table 24 summarizes several averages describing the trip episodes recorded. Duration per Trip summarizes all recorded trips (N = 11,379). The remaining descriptive statistics in Table 24 summarize trips with completed episode surveys (N = 9,134). Close Contacts are defined as individuals the participant regularly interacts with in person.

Table 24 below summarizes descriptive statistics describing the duration and distance of the average trip. The table also summarizes statistics about person-to-person contacts during the trip.

Table 25 summarizes the total number of trips recorded, categorized by primary mode type (the most used mode during a trip) and trip purpose (the activity type at the trip destination). The table compares all recorded trips to all trips with a completed episode survey. Participants specify the activity type before taking the episode survey; Daynamica is also able to predict the mode type without participant input based on speed and repeated trips that were previously labeled.

Table 24: Trip summary statistics.

Variable Name	N	Mean	SD	Min	Max
Duration per Trip (minutes)	11,379	20.24	34.84	0.48	1,283
Distance per Trip (miles)	11,379	7.83	15.49	0	259
Contacts per Trip	9,134	0.96	2.58	0	25
Contacts per Hour during Trips	9,134	7.06	35.41	0	1,800
Close Contacts per Trip	9,134	0.55	1.30	0	25
Close Contacts per Hour during Trips	9,134	4.39	22.94	0	1,320

Table 25: Trip summary statistics by trip mode and trip purpose (N = 8,904).

Variable Name	All Trip Episodes		Trip Episodes with Surveys	
	N	Percent	N	Percent
Primary Mode				
Bike	110	0.99	73	0.83
Bus	108	0.97	108	1.22
Car	8,603	77.48	7,067	79.87
Other	162	1.46	72	0.81
Rail	13	0.12	13	0.15
Walk	2,033	18.31	1,446	16.34
Trip Purpose				
Eat Out	542	4.72	498	5.63
Education	226	2.04	164	1.85
Home	4,203	37.85	3,507	39.64
Leisure and Recreation	1,283	11.56	1,112	12.57
Other	1,467	13.21	462	5.22
Personal Business	674	6.07	627	7.09
Shop	1,324	11.92	1,245	14.07
Work	1,239	11.16	1,115	12.60
No Trip Purpose	163	1.47	118	1.33

5.3.1 Trip Survey Statistics

Table 26 summarizes five questions from the trip survey. Trip environment asks participants how congested the environment was around the trip at its peak. Concerned with COVID-19 during trip asks how much participants agree with the following statement: for this trip, I am concerned with my risk of contracting coronavirus. Used preferred travel mode indicates that a participant selected “I used my preferred travel mode” instead of “I would have preferred using a different mode.” Same travel mode pre-COVID-19 asks participants if they would have used this transportation mode before coronavirus? Trip with car segment presents the total number of trips with a car segment recorded (including but not limited to trips with car as the primary mode). Trip with car segment and episode survey presents the total number of trips with a car segment and a completed episode survey. Considered transit for this trip asks participants if they would ever consider using public transportation for the trip recorded, yes or no, when a car segment is recorded during the trip.

Table 26: Trip survey summary statistics

Variable Name	N	Percent
Trip Environment		
Not Congested	7,161	81.00
Somewhat Congested	1,350	15.27
Congested	240	2.71
Very Congested	90	1.02
Concerned with COVID-19 during trip		
Strongly Agree	44	0.50
Agree	112	1.27
Undecided	282	3.19
Disagree	1,654	18.70
Strongly Disagree	6,752	76.35
Used Preferred Travel Mode	8,617	75.71
Same Travel Mode Pre-COVID-19	8,598	75.55
Trip with Car Segment	8,916	78.34
Trip with Car Segment and Episode Survey	7,105	62.43
Considered Transit Use for Trip with Car Segment	884	12.66

5.3.2 Regression Model — Trip Episodes

Table 27 presents the odds ratio estimates from logistic regressions of two dependent variables from the trip survey: the participant's concern with contracting COVID-19 during the trip; and the participant's consideration for using public transit for the trip in the future. Considered public transit only considers trips with a car segment.

Generally, a small proportion of recorded trips were associated with a concern with contracting COVID-19. A respondent is almost twice as likely to be concerned with COVID-19 during a short trip (5-10 miles). A respondent is more likely to be concerned with contracting COVID-19 as the number of contacts during the trip increases. There is no significant association with variation in close contacts. Four out of the seven trip purposes have a significant positive association with a concern with COVID-19. Respondents are more likely to be concerned with COVID-19 if the trip mode was something other than a car; although, bike did not have a significant result. No other variables had a significant association in this regression model.

Respondents are less likely to consider transit as the number of contacts increases for a particular trip but they are more likely to consider transit when those contacts are friends or family. Participants are over 70 percent more likely to consider transit use for trips with car segments to work. They are much less likely to consider transit for education trips; though very few trips for education were recorded. No other trip purpose had a significant association.

The chance that a respondent will consider transit use increases by 25 to 36 percent for short and medium distance trips but decreases by 40 percent for long trips, over 25 miles. Trip start time has a significant negative association in each category, likely influenced by the over 90 percent of trips that participants would not consider transit. The decrease in likelihood is greatest for trips that start at midday or in the evening. Participants are also 35 percent less likely to consider transit on weekends compared to weekdays. There are no sociodemographic or other previously considered variables that have significant associations in this regression.

Table 27: Odds ratio estimates for two logistic regression models for trip survey results. The value transformations for the two dependent variables are: Concerned with COVID-19 is a binary variable; 1 equals a participant that selected "agree" or "strongly agree" for any trip; for Considered Transit Use; 1 equals a participant selected "yes" for a trip with a car segment."

	Concerned with COVID-19	**Considered Transit Use**
Intercept	0.004*	2.986
Trip Level Data		
Trip distance (miles)		
Short Distance (5-10 Miles)	1.901°	1.248°
Medium Distance (10-25 Miles)	1.223	1.363*
Long Distance (25+ Miles)	0.672	0.590*
Contact Count	1.257***	0.720**
Close Contact Count	1.052	1.428**
Trip purpose		
Work	4.252**	1.747**
Education	1.435	0.037*
Shop	3.228**	0.850
Eat Out	1.069	1.057
Personal Business	3.389**	0.981
Leisure & Rec'n	1.585	0.935
Other	2.699°	1.208
Primary Trip Mode		
Transit	22.743***	NA
Walk	2.668**	0.318
Bike	0.000	NA
Other	10.670*	0
Trip start time		
Morning	2.361	0.556*
Midday	1.151	0.431**
Afternoon	1.602	0.530*
Evening	1.260	0.453**
Weekend	1.538	0.652***
Socio-demographics		
Female and gender nonconforming	0.977	1.083
Age 30-60	0.311	0.127

Age 60+	1.116	0.177
White	0.351	0.305
Asian	0.478	1.004
Black	6.954	2.778
Bachelor’s Degree or More	0.198	0.964
Unemployed/Other	0.455	1.193
Essential Worker	0.429	0.542
Job changes during COVID-19	0.602	0.302
Change in Pay/Hours COVID-19	4.722	0.786
Household Income > $50,000	0.967	0.351
Homeowner	1.249	1.865
Family Structure		
Live w/ Spouse	0.967	0.955
Lives w/ Child	1.355	0.31
Lives w/ Parents	4.092	0.171
Automobile Access		
More Drivers than Vehicles	0.816	0.751
No Working Vehicles	0.000	5.476
Health- and COVID-19-related conditions		
Very Good or Excellent Health	1.677	1.318
Disabled	1.464	0.259
Relevant Underlying Conditions	4.233	1.004
COVID-19 Major Threat to Self	1.450	1.388
Tested Positive for COVID-19 Before	0.551	0.196
Summary Stats		
R Squared	0.457	0.451
N	8,647	6,890

5.4 FURTHER EVALUATION OF ACTIVITY AND TRIP EPISODES

This section expands on trip and activity statistics, comparing them side-by-side. The information is collected from episode descriptive information and episode survey data.

5.4.1 Contacts and Close Contacts

Figure 19 below shows the average number of contacts for different activity and trip types along with 95% confidence intervals. Hourly contacts is a standardized quantity showing how the number of contacts varied based on hourly data instead of episode level. Larger confidence intervals are representative of data variability and low incidences. For instance, very few “Other” trips were recorded so there is a large confidence interval relative to other trip types with more incidences.

Results indicate that the average work activity had a higher number of contacts but this association is likely due to a larger average length. When standardizing contacts based on the duration, Work activities are more similar to other activity types while shopping activities become the highest on average.

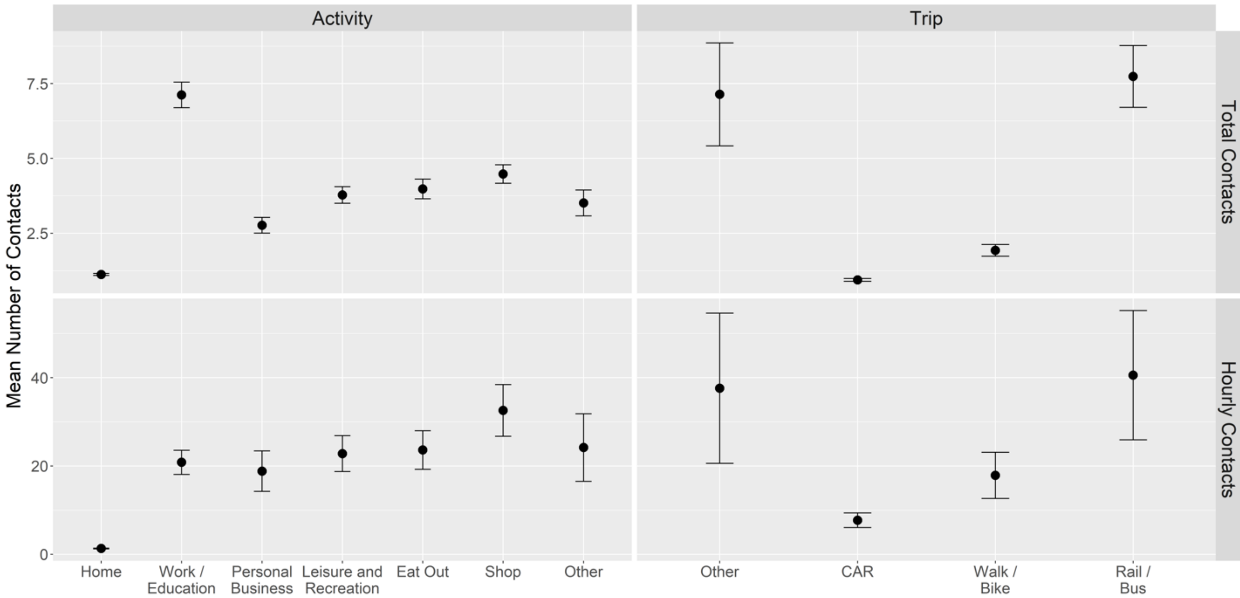


Figure 19: Mean number of contacts stratified by actitiy and trip type. Top panels refer to total contacts during activity or trip episodes. Bottom panels refer to contacts per hour for different activity and trip types.

Figure 20 displays the number of close contacts—individuals that a participant interacts with regularly. There is a similar trend as the previous figure but on a lower absolute scale. The most notable deviation was in Rail and Bus trips in which episode level contacts was lower for close contacts than regular contacts relative to the other trip modes.

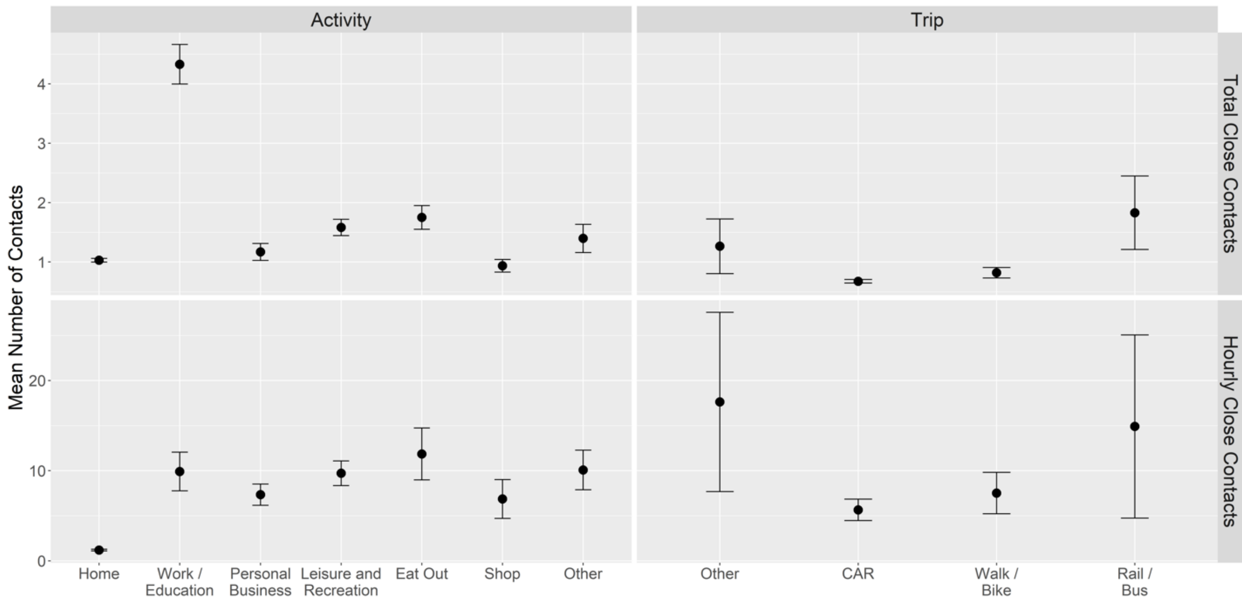


Figure 20: Mean number of close contacts stratified by activity and trip type. Top panels refer to total close contacts during activity or trip episodes. Bottom panels refer to close contacts per hour for different activity and trip types.

Figure 21 illustrates how time of day affects the average number of people a participant comes in contact with. Different lines depict different stratifications. The results are averaged across activity and trip types. Both women and men are more likely to come in contact with other people during the middle of the day on weekdays. Across all days, the number of contacts is primarily concentrated to the 8:00 AM and 6:00 PM period; although, the evening drop off occurs slightly later on weekends. Weekends also have a lower peak rate of contacts, and the peak occurs later in the day.

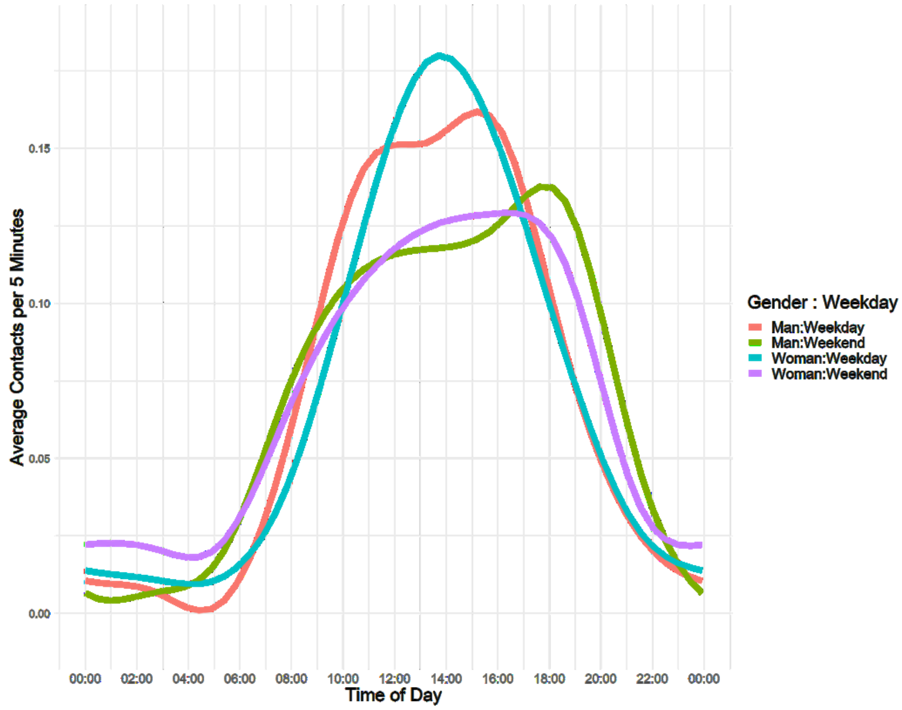


Figure 21: Average contacts by time of day. Lines refer to different stratificartions of gender and day of week.

Figure 22 on the next page shows average number of contacts for specific activity types. The Y axis refers to the average number of contacts per 5 minutes. In this case the lines depict specific activity types: Home, Work and Education, or all other Out-and-About activities (Shop, Eat Out, Personal Business, and Leisure & Recreation activities). The panels have stratified the data based on weekday or weekend days and by gender.

These figures illustrate dramatic differences in the average number of contacts over time depending on activity type and gender. Men have markedly different patterns in Work and Education activities between their weekdays and weekends distinguished by the occurrence of the curve’s peak. On the other hand, women in our sample did not have a clear, singular peak in the Work and Education curve. Women also had fewer contacts than men overall during Work and Education activities.

The Out-and-About curves have a similar pattern across the four stratifications; though, women have a slightly greater number of contacts than men during the peak, particularly on weekends. The rate of contacts during Home activities was nearly 0 regardless of the stratification.

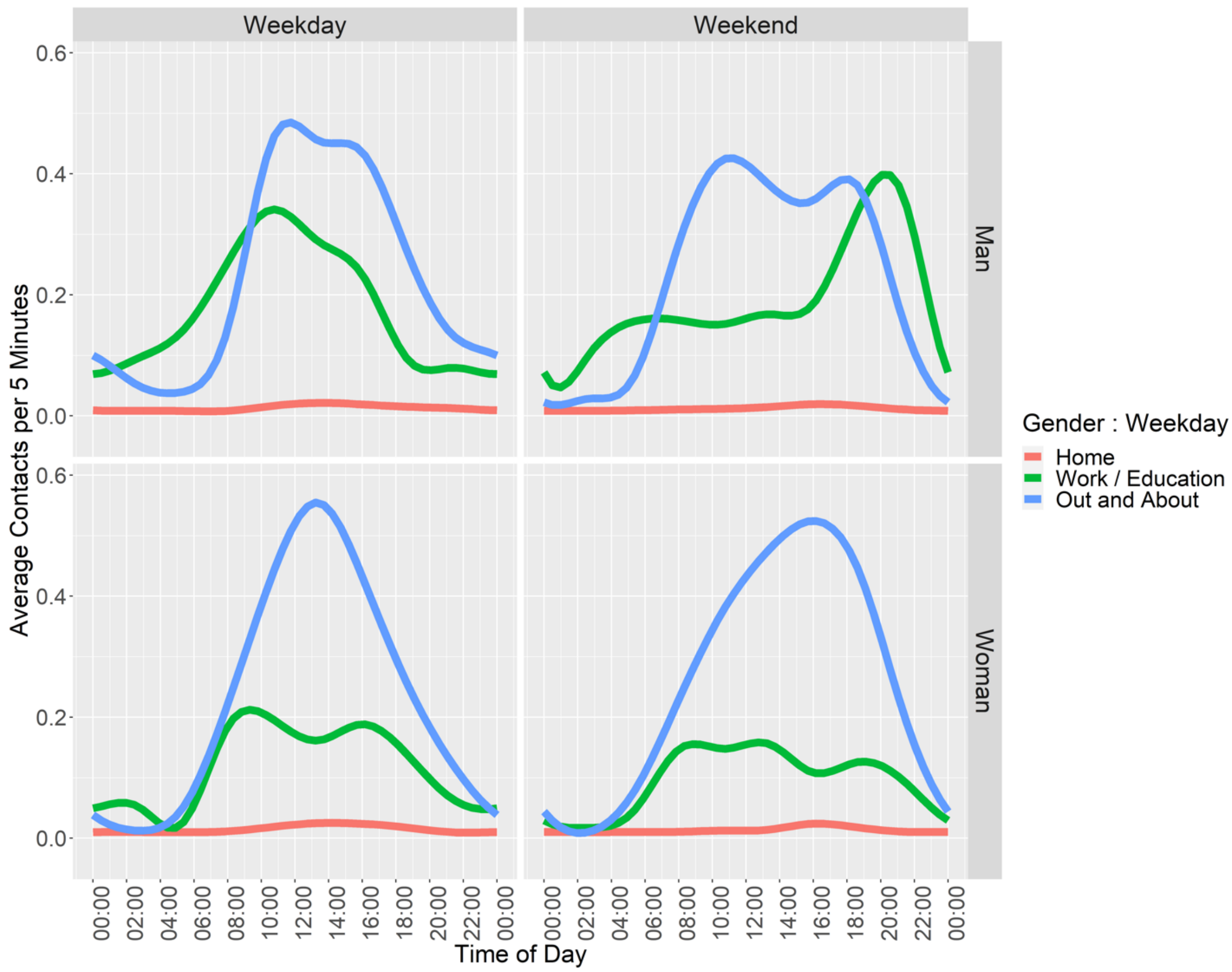


Figure 22: Average contacts by time of day. Plot panels are stratified by day of week and gender. Line color refers to different activity types.

5.4.2 Concern with COVID-19

The section presents data from trip and activity episode surveys, cross tabulating the numbers contacts encountered during the episode with the expressed concern with their risk of catching COVID-19. Figure 23 shows the average number of contacts with a 95% confidence interval stratified by the concern with COVID-19. Concern with catching COVID-19 appears to be strongly correlated with the number of contacts. People who are not concerned with contracting COVID-19 had much lower contacts on average.

Figure 24 illustrates the level of concern with catching COVID-19 stratified by different activity types and trip modes.

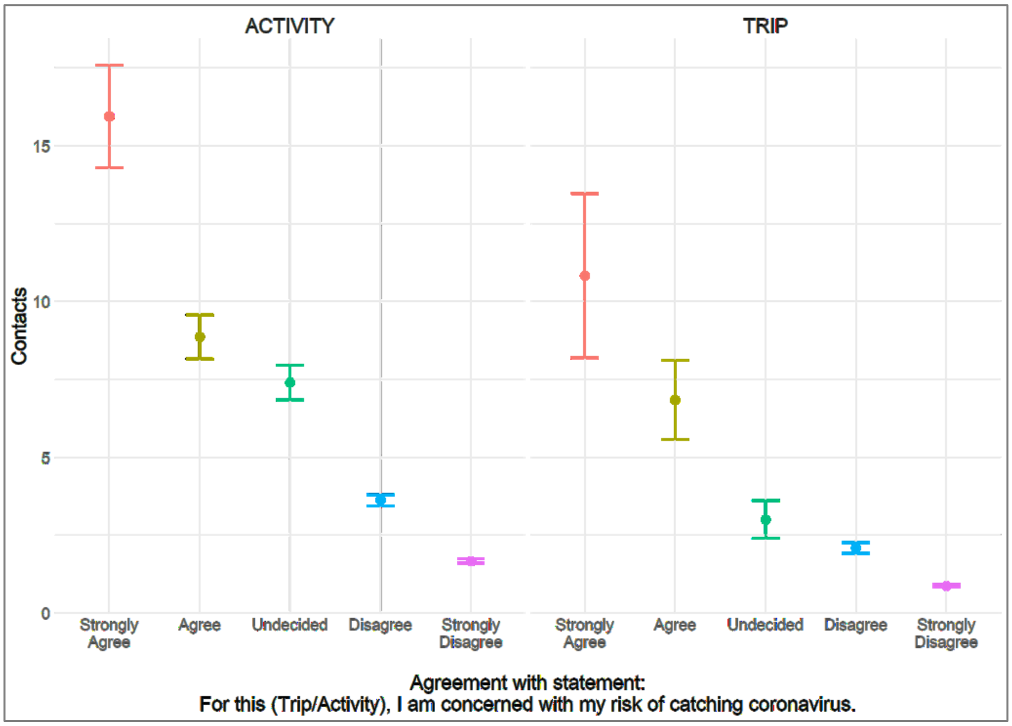


Figure 23: Mean number of contacts per activity, stratified by the concern level associated with the activity. 95% confidence intervals included alongside point estimates.

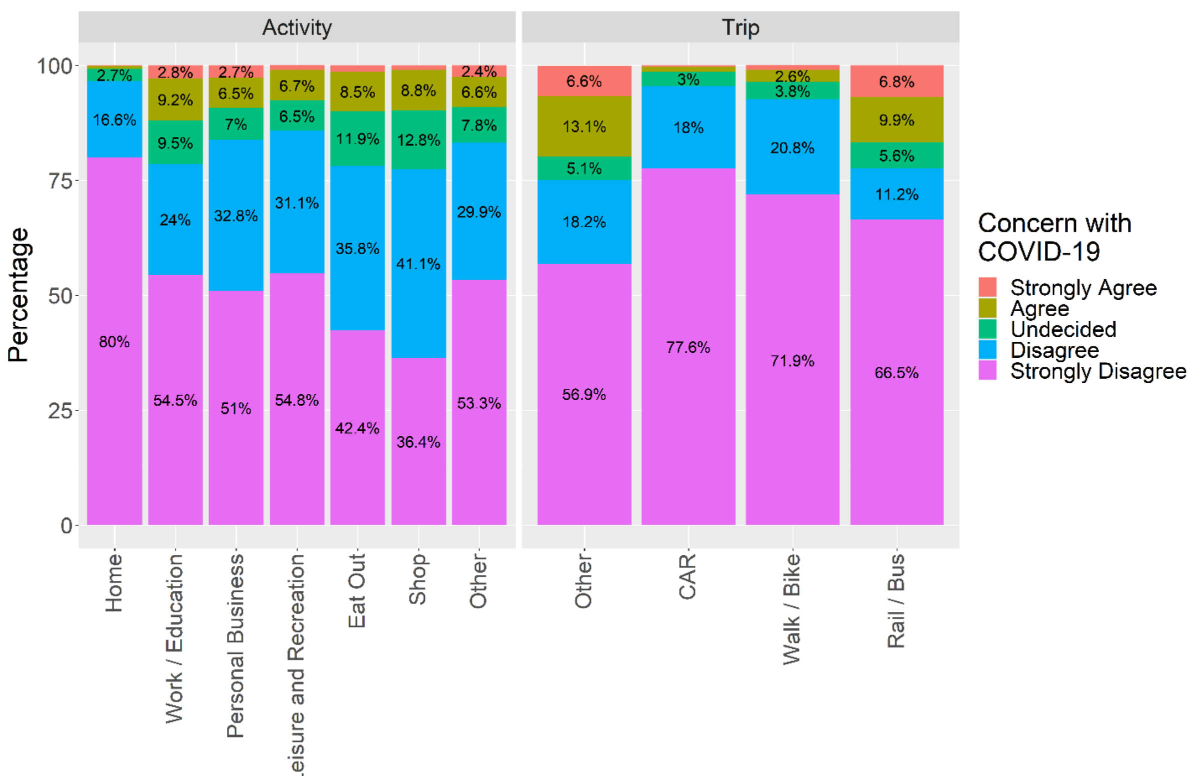


Figure 24: Relative frequency of levels of concern with COVID-19 for different activity and trip types.

5.4.3 Shopping Goods and Mode Use

Figure 25 below shows the different travel modes that were used for shopping trips. The shopping trips are separated by the reason for the shopping trip, meaning for which type of goods the participant was shopping. The reasons were not exclusive; a single shopping activity could have multiple reasons. The car is the most frequently used mode across all shopping goods. Much of the variation in the percentage of mode use is a trade-off between car use and walk or bike use. Participants were more likely to walk or bike for takeout food than for other shopping goods. Participants were least likely to walk or bike for "other essential items."

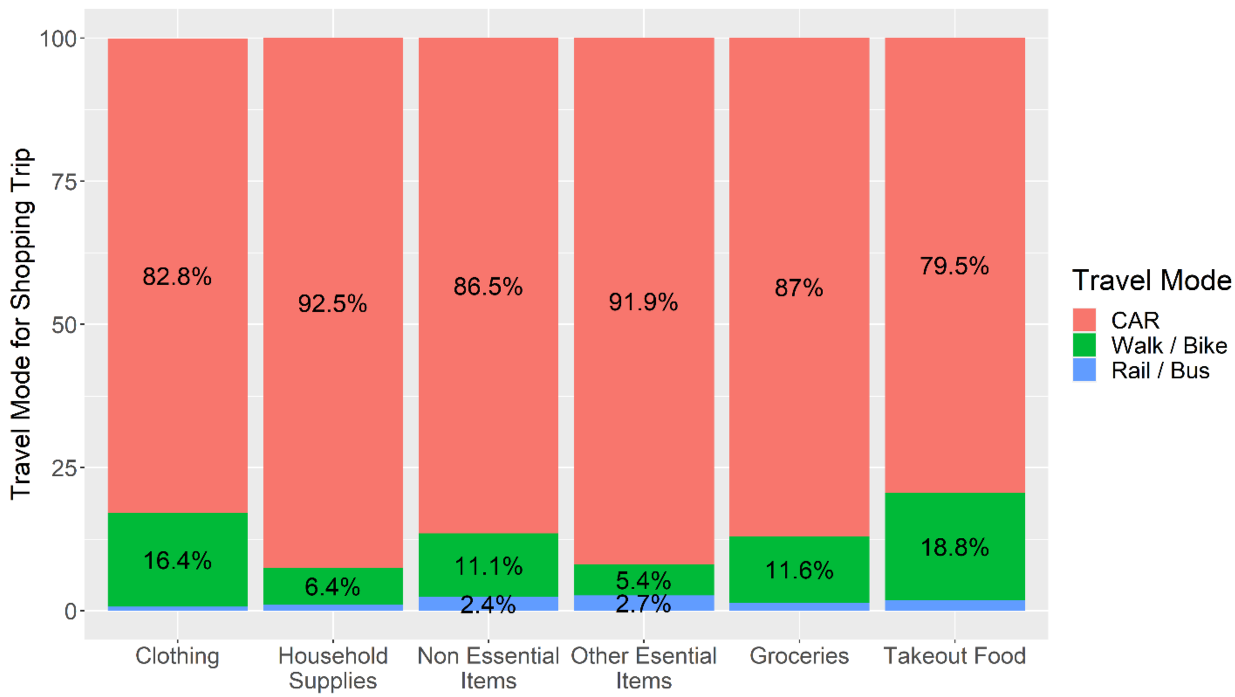


Figure 25: Common travel modes by reason for shopping activity.

5.4.4 Trip Origin-Destination Pairs

Here, we present cross-tabulations that display origin and destination pair frequencies for three trip characteristics: number of trips, distance per week in miles, and time per week in minutes. Each cross-tabulation presents the pair frequencies for all days, weekdays only, and weekends only. Figure 26 presents the pair frequency for the number of trips per week. The figure illustrates that trips most frequently start or end at home. The next most frequent trip pairs are those involving shopping (Shop) or leisure and recreation (Leisure & Rec'n); it's more likely that trips will start or end with these activity types during the weekend. This trend can also be observed in Figures 27 and 28 which present the pair frequencies for distance per week and time per week. Personal Business activities are more prominent in the distance and time tabulations than the trips per week tabulation.

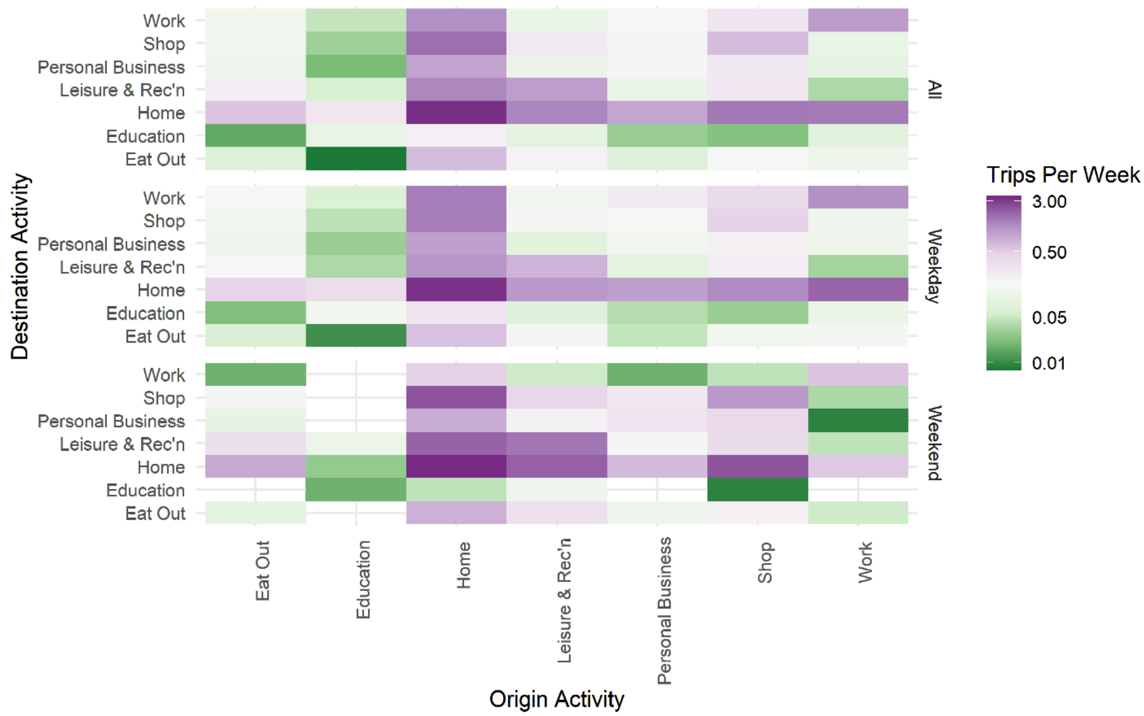


Figure 26: Number of trips per week organized by origin and destination activity.

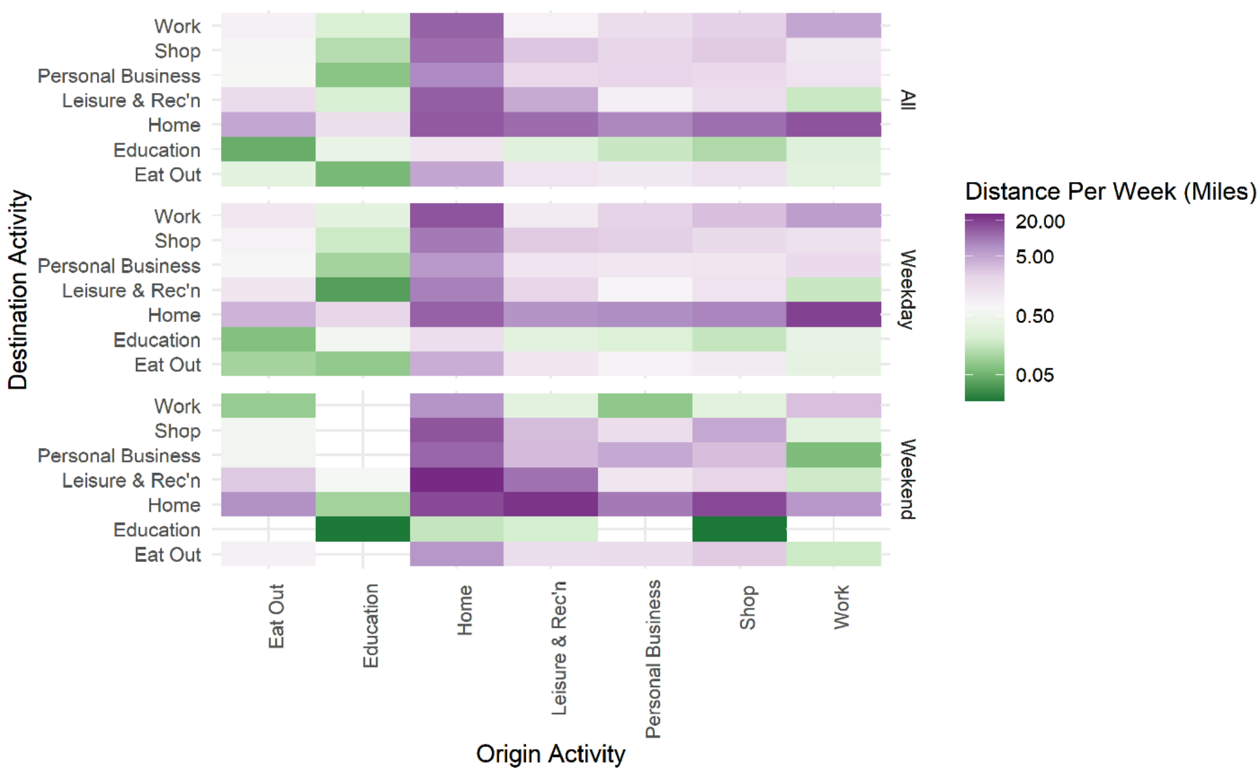


Figure 27: Number of miles traveled per week organized by origin and destination activity.

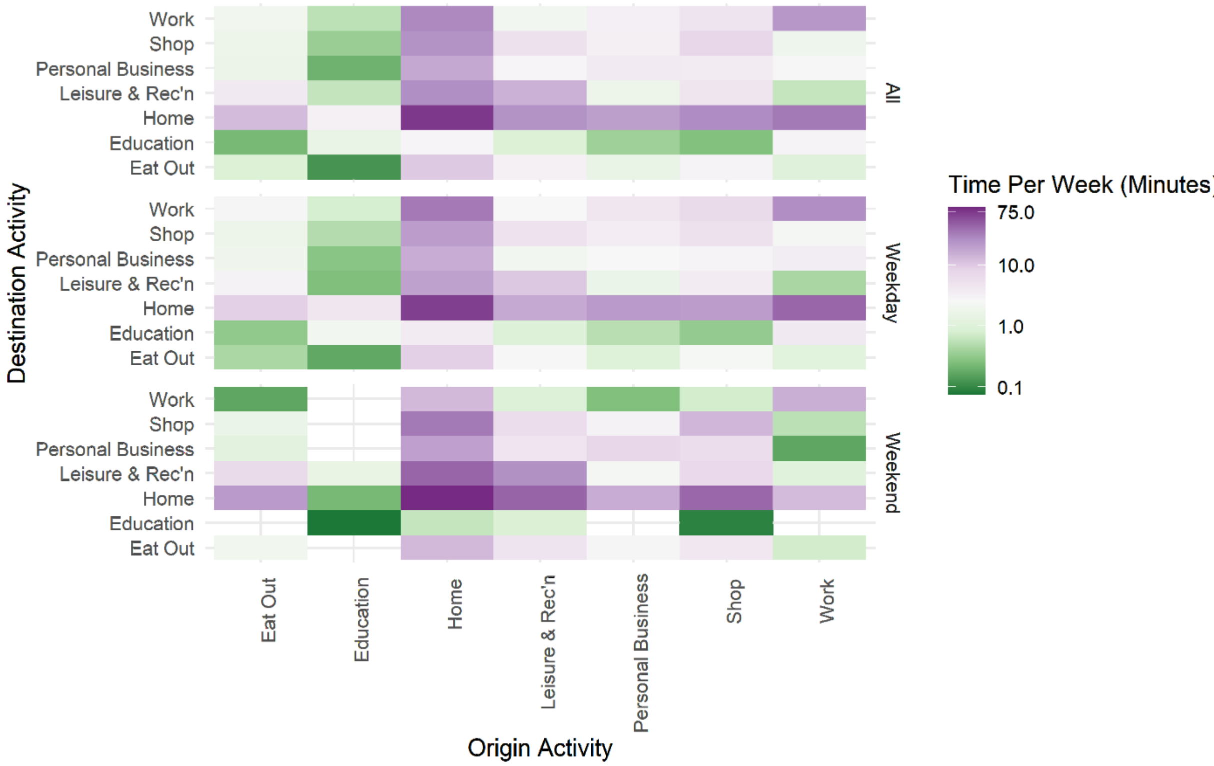


Figure 28: Number of minutes traveled per week organized by origin and destination activity.

This concludes the presentation of the daily activity-trip behavior data and the in-app survey data collected with the Daynamica app from study participants. This chapter summarized the data collected each day, and during each activity and trip. These variables, along with variables presented in Chapter 4, were used in the logistic regression of several dependent variables from the episode surveys. These results provide a preliminary indication for how downtown Minneapolis commuters are responding to the COVID-19 pandemic and how that response could be shaping their travel behavior. The next chapter will explore the causal effect of the COVID-19 pandemic on two time-use metrics, utilizing historical Daynamica data collected from a previous study.

CHAPTER 6: CAUSAL ANALYSES OF COVID-19 IMPACTS ON ACTIVITY AND TRIP PATTERNS

In this chapter, we explore the causal effect of the COVID-19 pandemic on two time-use metrics, utilizing historical Daynamica data collected from a previous study. The first metric summarizes the activity patterns the study population engaged in throughout the day, examining the frequency and ordering of activities. The second metric focuses on the probability of engaging in a certain type of trip or activity throughout the day. These analyses will explore the interaction between causal effect of COVID-19 and time of day.

In order to evaluate the causal effect of COVID-19 on activity patterns and other behavior, we must identify a dataset which can represent data pre COVID-19 or if COVID-19 had never happened. To address this, we will be using data collected in the Minneapolis-St Paul (MSP) metropolitan area from October 17, 2016 to October 25, 2017 (Fan et al., 2019). This 2016-2017 (MPLS) study collected data from 398 residents with diverse socio-economic backgrounds in six neighborhoods in the Twin Cities metropolitan area.

Because our data is observational and participant recruitment was performed using convenience sampling, we must account for the differences in the study recruitment and overall study populations in order to produce unbiased measurements on the effect of COVID-19. While unadjusted analyses are expected to be relatively accurate, alternative Causal Methods will allow us to determine the direct effect of the COVID-19 pandemic while accounting for variations in the study design and different demographic breakdowns in the Daynamica studies. Using these analysis tools, we will be able to identify the specific effects of COVID-19 on the residents of the Twin Cities metropolitan area.

Throughout this chapter, the results will be presented via three different analysis methods. The first is an unadjusted analysis which is not considered a causal method. This is included to specifically illustrate the effects of specific causal methods to modulate the unadjusted estimates as well as verify that the causal estimates are not unreasonable. In general, we expect the results of the causal methods to be relatively similar to the unadjusted analysis. This is because the two studies that were conducted were similar and the demographic breakdown of the two studies was not drastically different.

The other two approaches for generating causal estimates are Inverse Probability Weighting and Propensity Score Stratification. In general, these account for the demographic breakdowns in studies by computing a probability of being in CTI vs the pre-COVID-19 (MPLS) study and using this probability to compute weighted means or stratify the data based on the probability and computing means within subgroups respectively. Specific details on these causal estimators can be found in Hernan and Robins (2020).

In general, causal analysis operates by adjusting for confounders which are associated with both the outcome and the treatment variable, which in our case, is which study the individuals participated in. These confounders are the primary metrics which may have influenced whether individuals participated in this study compared to the previous study as well as the outcome. The confounders that we will be using are:

- Gender (Man vs Woman/Other)
- Employment Status (Employed Full Time vs Unemployed/Other)
- Age (Numeric)
- Education (Highschool or Less, Some College, Bachelor's Degree or More)
- Income (Less than $50,000 vs More than $50,000)
- Own Home (Yes / No)
- Race (White Indicator, Black Indicator, Asian Indicator)

It is assumed in this analysis that after adjusting for these demographic variables, which study you participated in has no influence on the causal effect estimate. This is a standard assumption in causal analysis and is reasonable assumption in our case as well. In all analyses, our confidence intervals are computed using a bootstrap resampling approach with a 5% Type 1 Error rate.

6.1 ACTIVITY CHAINS

The first analysis of this chapter is related to exploring aggregate measures of how individuals spent their days. This will allow us to evaluate population level patterns to see how general trends changed with COVID-19. In order to evaluate activity patterns, we will summarize our data into Activity Chains, a new method for summarizing activity-trip data which was first introduced for analyzing Daynamica data in Fan et al. (2020).

Activity Chains are strings of characters representing what sequence of activities individuals engaged in throughout the day. The chains are generated using the following algorithm.

- 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.

It should be noted that this is just one approach to construct activity chains and alternative approaches are also viable and can provide insightful results as well.

Activity Chains can be evaluated in two primary ways. The first is to evaluate the relative probability of a chain being observed on a given day compared to all other chains. Table 28 summarizes the 25 most popular activity chains in the CTI study, outlining how frequently these chains occurred in CTI (Post COVID-19) and the MPLS (Pre COVID-19) study. Additional columns provide information on the Unadjusted Effect and the Causal Effect using the inverse probability weighting (IPW) and propensity score stratification (PSS) estimators and the 95% confidence intervals.

Table 28: Activity Chain frequency pre and post COVID-19 pandemic with causal differences

Activity Chain	Post COVID-19 Frequency	Pre COVID-19 Frequency	Unadjusted Effect	IPW Causal Effect	PSS Causal Effect
H	29.0	18.2	10.8 (7.8, 16.7)	12.8 (7.9, 17.8)	12.3 (8.1, 17.4)
HOH	18.1	15.3	2.8 (-0.8, 6.9)	4.2 (0.2, 8.4)	4 (0.1, 7.9)
O	17.5	9.4	8.1 (1.7, 12.8)	9.4 (3.2, 16.6)	9 (3.5, 15.3)
HSH	11.1	9.7	1.4 (-2, 4.4)	-0.9 (-4.2, 2.5)	-0.7 (-3.8, 2.5)
HOHOH	3.4	4.7	-1.3 (-3.1, 0)	-1.1 (-2.6, 0.4)	-1.2 (-2.8, 0.2)
HSOH	2.8	4.1	-1.3 (-2.9, 0.3)	-2 (-3.7, -0.4)	-2 (-3.6, -0.4)
HO	2.5	5.9	-3.4 (-5, -2.1)	-3.3 (-4.8, -1.8)	-3.1 (-4.6, -1.7)
OH	2.0	4.0	-1.9 (-3.2, -0.7)	-1.6 (-2.9, -0.4)	-1.7 (-2.9, -0.4)
HSHOH	1.3	2.4	-1.1 (-2.1, 0)	-1.6 (-2.9, -0.5)	-1.6 (-2.8, -0.5)
S	1.2	1.3	-0.1 (-1.2, 1.2)	-0.6 (-1.9, 0.6)	-0.3 (-1.5, 0.8)
SH	1.2	1.7	-0.5 (-1.4, 0.4)	-0.7 (-1.7, 0.2)	-0.6 (-1.6, 0.2)
HS	1.1	3.2	-2.1 (-3.2, -1)	-2.4 (-3.7, -1.2)	-2.3 (-3.5, -1.2)
SOS	0.8	0.3	0.5 (-0.3, 1.5)	0.5 (-0.3, 1.6)	0.6 (-0.2, 1.5)
HOHO	0.6	1.2	-0.6 (-1.2, 0.1)	-0.6 (-1.3, 0.1)	-0.5 (-1.3, 0.1)
HOSH	0.5	1.1	-0.6 (-1.3, 0)	-0.6 (-1.3, 0)	-0.7 (-1.4, 0)
OHOH	0.5	0.7	-0.1 (-0.7, 0.4)	-0.1 (-0.7, 0.4)	-0.2 (-0.8, 0.4)
HSO	0.4	1.5	-1.1 (-1.8, -0.5)	-1.3 (-2, -0.6)	-1.3 (-2.1, -0.6)
SHS	0.4	0.1	0.2 (-0.2, 0.8)	0.1 (-0.2, 0.6)	0.2 (-0.2, 0.7)
HOHOHOH	0.3	0.5	-0.2 (-0.8, 0.2)	-0.2 (-0.6, 0.2)	-0.2 (-0.7, 0.2)
HOHSH	0.3	0.6	-0.3 (-0.8, 0.1)	-0.3 (-0.8, 0.2)	-0.3 (-0.8, 0.2)
HSHO	0.3	0.9	-0.6 (-1.2, -0.1)	-0.8 (-1.5, -0.2)	-0.7 (-1.5, -0.2)
HSHSH	0.3	0.6	-0.3 (-0.9, 0.2)	-0.3 (-0.8, 0.2)	-0.3 (-0.9, 0.2)
HSOSH	0.3	0.5	-0.2 (-0.6, 0.3)	-0.2 (-0.7, 0.3)	-0.1 (-0.7, 0.3)
OS	0.3	0.5	-0.2 (-0.7, 0.3)	-0.2 (-0.8, 0.2)	-0.2 (-0.8, 0.3)
OSO	0.3	0.9	-0.6 (-1.3, 0.2)	-0.4 (-1.1, 0.2)	-0.5 (-1.2, 0.2)

The other way of evaluating activity chains is to explore the conditional probability of the next event occurring in the chain given the current state of the chain. For example, we may be interested in the relative frequency chains proceeding to O given that they started in H. Figures 29 and 30 highlight the conditional relative frequencies for both Pre and Post COVID-19. These figures show unadjusted rates and are not causal estimates.

Within these two figures, the relative frequency of Activity chains is visualized by the width of bands and the color indicates the type of activity within the activity chain. These figures are pruned at 1% meaning that if an Activity Chain did not occur at least 1% of the time, it was omitted from the visualization. Finally, an “X” was included at the end of activity chains. This was done to differentiate between fully terminated chains and chains that were pruned early because of infrequency.

Based on the two figures, it is clear that the diversity of chains greatly diminished because of COVID-19 with a much higher rate of “H” chains. In fact, we estimate that the causal effect of COVID-19 resulted in an increase in the rates of days in which individuals not leaving their home of 13.3% (95% CI: 8.5, 18.5). We also can see that individuals were much less likely to travel to work (sustenance) during COVID-19 and individuals were more likely to go directly home following work (sustenance) compared to Pre COVID-19.

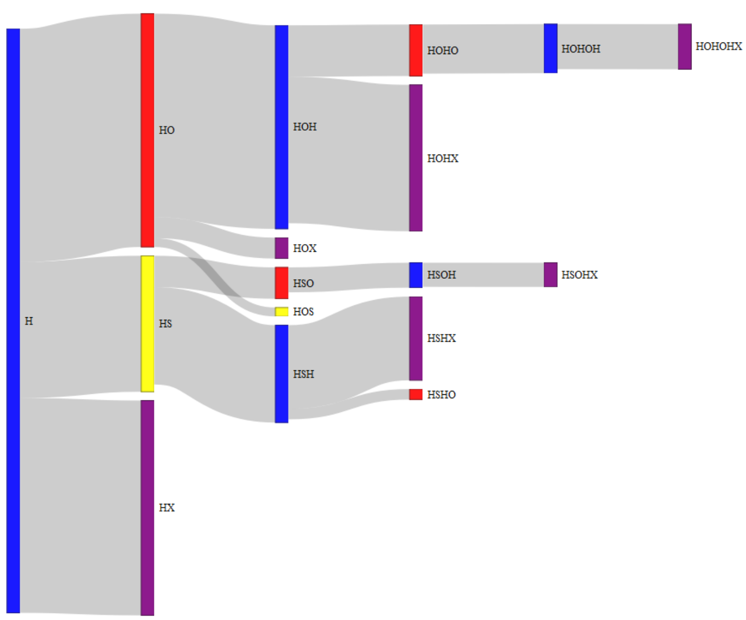


Figure 29: CTI Chains from Post-COVID

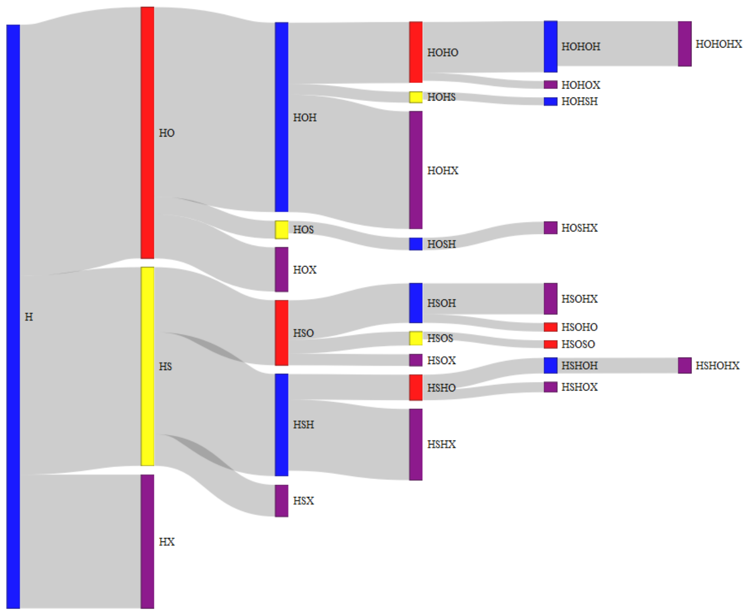


Figure 30: MPLS Chains from Pre-COVID

In addition to examining the relative frequency of different chains, we also explored the probability of specific elements existing within the chain. Specifically, we explored the probability that chains contained at least one sustenance (S; work/education) or contained at least one out-and-about (O) activity. We evaluated the respective causal effect of these two scenarios and present the results in Table 29. We are able to explore whether the frequency with which people engaged in sustenance or out-and-about activities at all in a day changed because of COVID-19. The results reiterate the idea that the diversity of activity chains dropped significantly following COVID-19 and individuals did not go to sustenance nor out-and-about at any point during their day as frequently. The overall effect was a drop of almost 20% in terms of frequency (95% CI: -24.1, -13.4). Almost 10% fewer activity chains contained an out-and-about event at any point in the activity chain.

Table 29: Relative frequency of activity chains containing Work or Out and About activities with causal differences.

Activity Chain	Post COVID-19 Frequency	Pre COVID-19 Frequency	Unadjusted Effect	IPW Causal Effect	PSS Causal Effect
Contains “S”	25.7	39.2	-13.5 (-19.6, -8.1)	-19 (-24.1, -13.5)	-17.9 (-23.5, -13)
Contains “O”	55.6	65.0	-17.9 (-23.5, -13)	-9.4 (-19.5, -8)	-19 (-24.1, -13.5)

These results highlighted major differences in activity patterns across the Twin Cities Metro population when aggregating to the sequence of unique day level activities. The overall diversity of unique types of activity chains decreased dramatically, with chains being shorter and many more individuals spending the entire day at home.

This concludes the analysis on the causal effect of COVID-19 on metrics related to activity chains. In the next sequence of analyses, we will explore a new metric to summarize activity and travel patterns to better understand the effects of COVID-19.

6.2 PROBABILITY OF ENGAGING IN ACTIVITIES/TRIPS THROUGHOUT THE DAY.

This section focuses on determining how COVID-19 effects what people do throughout the day. This analysis will eschew the sequential nature of the previous Activity Chains and instead focus on the causal effect in relation to time of day. Using similar labels as before along with a trip label, H, O, W (work), and T, we will explore the probability of a person engaging in these categories at a given time of day. These causal effects will be stratified based on time of day and whether the day is a weekday or weekend.

The results are summarized in a collection of 3 figures related to the 3 different analysis methods: Unadjusted, IPW, and PSS. The figures are all formatted identically with 6 panels arranged in a grid of 3 columns and 2 rows. The top row is for the effects for weekdays only and the bottom row for weekends only. The first column is the probability of engaging in certain activities throughout the day during COVID-19 only. The middle column is for Pre COVID-19 or if COVID-19 never occurred. The final column is the specific causal effect of COVID-19 or the difference between the previous two columns.

Within each panel of the figures, there are four unique solid curves. These indicate the probability over time of a person engaging in a given activity or trip type. For instance, the "Home" curve is about 0.9 at 7:00 AM, meaning a person has a 90% change of being at home on average at that time during the COVID-19 pandemic. The dashed lines indicate the confidence intervals. In all cases, the lines are actually LOESS smoothed estimates of point estimates at time points. Lines are provided instead of points to make the plots more interpretable and to reduce noise. Likewise, tables are not provided in terms of results because of the total amount of information contained within each plot.

Overall, all figures, regardless of the methods, tell a similar story. This is similar to the Activity Chains analysis and highlights that the specific effects of the confounders were limited in this analysis. For this analysis, we will specifically focus on analyzing the results from the IPW analysis figure.

These figures allow for many unique insights into time use patterns and how they changed with COVID-19. Not only can we explore how the probability of engaging in certain activity types changed because of COVID-19 but also how these rates changed relative to one another.

During COVID-19 (the left most column), the "Home" curve (green) is significantly higher than any other curve displayed. This shows that the probability of being at home was larger than engaging any other activity type, regardless of the time of day. While it was always higher, the amount that it was higher slightly decreased during typical work hours between 9AM – 3PM. During that time, there was a commensurate increase in the probability of being at work during the weekdays (top row of figure). We can see from the second column that the probability of being at home was significantly less prior to COVID-19 and other activities were more likely throughout the day. On weekdays, Work was much more likely than Home during regular working hours. Out-and-About activities were about equally likely as

Home during work hours but saw a sharp increase during the late evening across all days. During the weekend, the probability of engaging work remained relatively low regardless of whether it was prior to COVID-19 or during COVID-19.

Using the final column of the figure, we may see the specific causal effect on the change of the probability at a given time point. In these cases, if the line is close to 0 then there was little to no causal effect and if the dashed line contains 0, then the effect is not statistically significant different from 0. Across all hours of the day, there was a statistically significant effect on the probability of engaging in a Home activity, around a 50% absolute increase when COVID-19 began. There was a similar decrease in probabilities for the other activity types. The causal effects between weekdays and weekends look extremely similar indicating the effect of COVID-19 on these probabilities was not different based on the day of the week but reflective of the baseline underlying probabilities prior to COVID-19.

For Out-and-About activities, there was a dramatic decrease in the probabilities during the evenings. This highlights that individuals reduced the frequency with which they engaged in evening activities during the COVID-19 pandemic.

All three figures provide very similar results in all of these respects with minor differences in the general shape to the curves. A primary difference between these figures is at the tail end of each curve, close to 6:00 AM or 11:00 PM. In some cases, the plots show steeper changes at the edges of the graph. These differences should not be ignored as artifacts of the smoothing process and not indicative of deviations in the model.

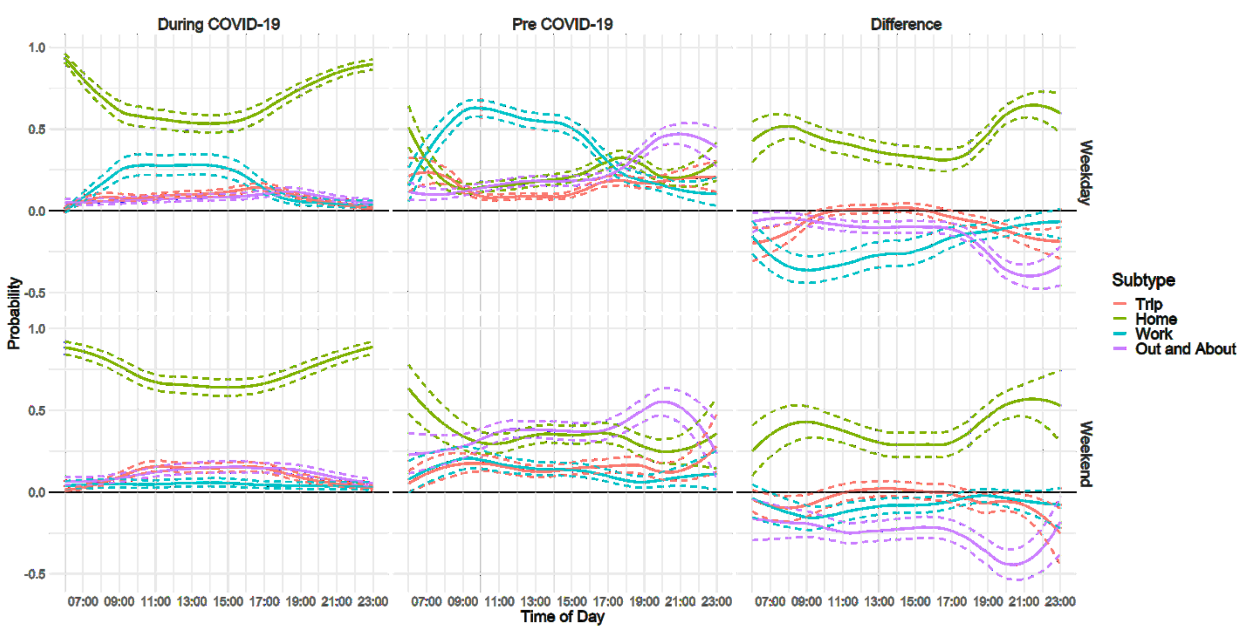


Figure 31: Inverse probability weighting causal estimates of probability of engaging in activity type by time of day by day of week and pre/post COVID-19.

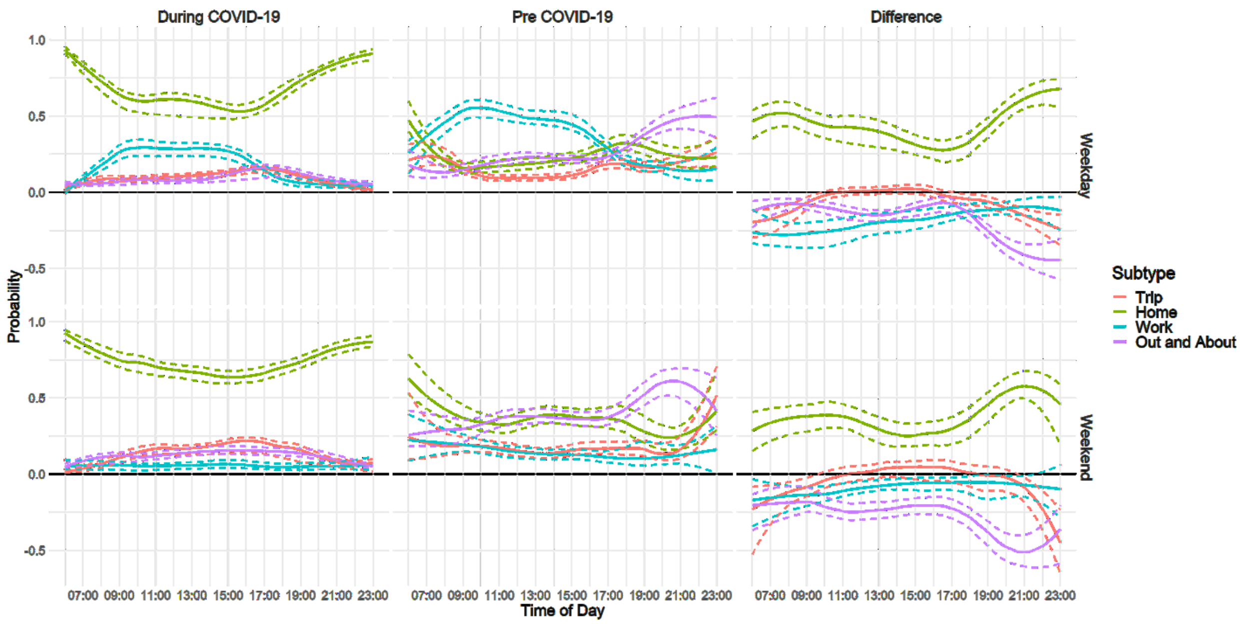


Figure 32: Propensity score stratification causal estimates of probability of engaging in activity type by time of day by day of week and pre/post COVID-19.

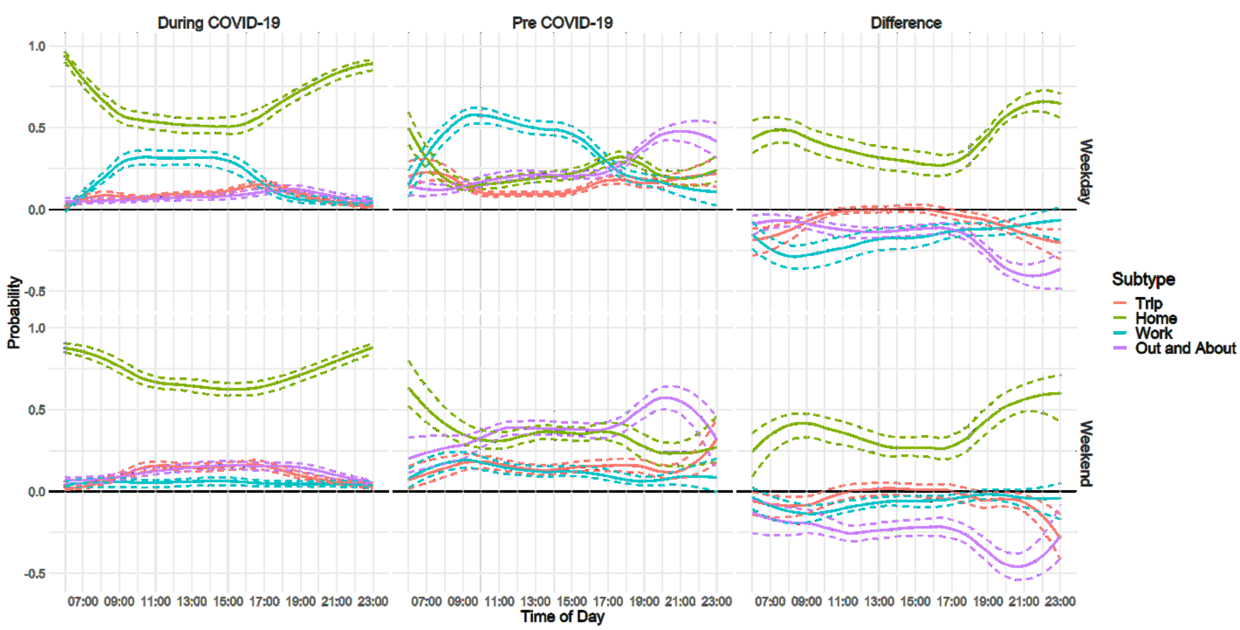


Figure 33: Unadjusted estimates of probability of engaging in activity type by time of day by day of week and pre/post COVID-19.

This chapter sought to provide unique insights on the effect of COVID-19 on time use patterns. Using historical data and causal methods, we determined the specific effect of COVID-19 on these time-use patterns. We learned that COVID-19 resulted in significantly less variable Activity Chains with a much higher proportion of H activity chains than previously. Likewise, the effects of COVID-19 at specific times of the day were quite dramatic with individuals now spending the majority of their time at home throughout the day. The next chapter concludes this report.

CHAPTER 7: CONCLUSIONS

This research aimed to collect original data on how COVID-19 may be shaping the travel behavior decision-making process among downtown Minneapolis commuters at the individual and trip levels. Understanding the travel behavior decision-making process of commuters in response to COVID-19 is a critical step in identifying innovative and timely strategies for local transit providers to regain their market share and ridership after the COVID-19 pandemic.

This research recruited a sample of downtown Minneapolis commuters to record detailed travel behavior decision-making data at the individual trip level during the spring of 2021. Travel behavior decision-making data was recorded with a customized mobile app on the participants' smartphones. Most studies examining mobility impacts of COVID-19 have used secondary smartphone location data to quantify the amount of travel reduction in response to the COVID-19 crisis. Although informative, such data did not have the granularity and level of detail to uncover the underlying travel behavior decision-making process.

Existing literature illustrates a reduction in ridership among shared modes, particularly public transit. However, researchers have identified socioeconomic disparities in how the pandemic affected travel behavior and public transit use. Lower-income and less-educated riders were more likely to have in-person jobs and thus were more likely to have persistent transit demand throughout the pandemic. There were also unequal overall transit trip reductions when looking at trip purposes. Social, recreation, and worship destinations saw the greatest reductions while shopping and work destinations saw the smallest reductions. Neighborhood isolation also increased during the first few months of the pandemic, trips to central business districts especially declined. Groups encountering transportation barriers prior to the pandemic, including women and people in poor health, were observed to be more likely at a disadvantage during the pandemic while avoiding public transit. One logistic regression of transit demand found that being a female, having kids, and being married had a significant correlation with a greater reduction in trips.

Chapter 4 presented regression models to examine sociodemographic characteristics associated with COVID-19-related travel behavior and perception changes, including changes in frequency of types of trips made (Table 5), experience of hardships during the pandemic (Table 6), typical commute mode during the pandemic (Table 7), willingness to use a particular mode for commuting (Table 8), preferences for both COIVD-19 related safety measures on public transit (Table 9), general public transit service improvements (Table 10), and overall interest in using public transit and comfort while doing so before and during the pandemic (Table 11). We found that the number of respondents not interested in using transit almost doubled over the period before March 2020 to the time of the survey, while the number of respondents not comfortable with transit more than doubled over the same period.

Chapter 5 presented descriptive statistics from episode characteristics and episode surveys recoded with the Daynamica app. Episodes included a day, an activity, and a trip. Regression models were also presented with characteristics from each episode type to examine questions such as concern with COVID-19 and daily travel behavior post-COVID-19. Table 19 presented regression results from End-of-

Day survey data including whether the participant experienced a transportation barrier that day. Table 23 presented regression results from the Activity survey data including concern with COVID-19, activity importance, and activity timeliness. Table 27 presented regression results from the Trip survey data including concern with COVID-19 and whether the participant considered transit use.

Chapter 6 explored the causal effect of the COVID-19 pandemic on two time-use metrics, using historical Daynamica data collected from a previous study. The first metric summarized the activity patterns the study population engaged in throughout the day, examining the frequency and ordering of activities. The second metric focused on the probability of engaging in a certain type of trip or activity throughout the day. We learned that COVID-19 resulted in significantly less variable Activity Chains with a much higher proportion of days spent just at home than before the pandemic. Likewise, the effects of COVID-19 at specific times of day were quite dramatic with individuals now spending the majority of their time at home throughout the day.

This research helps identify inter- and intra-individual differences in the mobility impacts of COVID-19 by collecting primary travel behavior decision-making data from individuals with varied socio-demographics and across multiple trip environments. The findings will help transportation planners identify innovative and sensible ways to promote the use of public transportation in the post-pandemic era.

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APPENDIX A:
INTAKE SURVEY

Section 1: Consent Form and Eligibility Criteria

Thank you for your interest in the COVID Travel Impact (CTI) Study and thank you for helping the University's research mission to evaluate mobility impacts of the new contracts. Please complete this 15-minute enrollment form which helps us verify your eligibility to participate in this study. You will be asked to provide consent to participate in the study and complete a brief background survey.

1. Are you over 18 Years Old?
    a. Yes
    b. No *(End Survey)*
2. Do you live in Twin Cities (Minneapolis-St. Paul) Metropolitan Area?
    a. Yes
    b. No *(End Survey)*

[Consent form was displayed to participant]

3. If you consent to participate, please sign below:
    a. Signature Entry
4. Please enter your Full Name
    a. Free Text Entry

Section 2: Background Information

Thank you for choosing to participate. The remaining questions of this survey will focus on background information about yourself. After completing this survey, you will receive an email about how to install the Daynamica smartphone app on your phone.

5. What name would you like to be referred to in communications?
    a. Free Text Entry
6. Please provide an email address the study can use to contact you. This email will also be used to provide compensation upon your completion in the study.
    a. Free Text Entry
7. What is your age?
    a. Numeric (18 – 100)
8. What is your gender?
    a. Woman
    b. Man
    c. Non-binary/Third Gender
    d. Prefer to Self-Describe (Free Text Entry Allowed)
    e. Prefer Not to Answer
9. What best describes your Race or Ethnicity (Select all that apply)
    a. American Indian or Alaska Native
    b. Asian
    c. Black or African American
    d. Hispanic, Latino, or Spanish Origin

e. Middle Eastern or North African
f. Native Hawaiian or other Pacific Islander
g. White
h. Other race, ethnicity, or origin

10. What is your highest level of education?
    a. Less than a high school diploma
    b. High School Diploma
    c. Some College
    d. Associate's Degree
    e. Bachelor's Degree
    f. Graduate/Professional Degree
11. What type of phone do you use?
    a. Apple
    b. Android
    c. Other: Please specify *(Free text Response)*
12. What zip code do you live in?
    a. Free Text Response

Section 3: Employment Information

Employment Questions:

The following questions focus on details about your current and past employment situation.

13. As of **today**, what is your employment status?
    a. Employed Full Time
    b. Employed Part Time
    c. Unemployed Looking for Work
    d. Unemployed Not Looking for Work
    e. Retired
    f. Primarily Self-Employed
    g. Unpaid Volunteer or Intern
    h. Homemaker or Stay at Home
14. *(If Q13 == a, b, f, g)* Do you work in any of the following fields:
    - Building maintenance and repair (e.g., electrician, plumber)
    - Defense
    - Delivery and postal service
    - Grocery, pharmacy, convenience
    - Human services (e.g., food bank, homeless shelter)
    - Manufacturing
    - Medical and health care
    - Public safety (e.g., law enforcement, fire, security, EMT)
    - Sanitation
    - Transportation and logistics
    - Utilities (e.g., water, electricity)
    - Other essential services

    a. Yes
    b. No

15. *(If Q13 == a, b, f, g)* As of **today**, which of the following best describes your **current** work location?
    a. Work ONLY from home (self-employed or only telework)
    b. Telework some days and travel to a work location for the remainder
    c. Only one work location (outside of home)
    d. Work location is outside of home and regularly varies (different offices/job sites)
    e. Drive/bike/travel for work (driver, sales, deliveries)
16. *(If Q15 != a)* As of today, how are you typically travelling to and from work? (Select all)
    a. In a household vehicle (or motorcycle)
    b. In another vehicle (e.g., rental, carshare, friend's vehicle, work vehicle)
    c. In a taxi or ride service (e.g., Uber, Lyft)
    d. In a bus or shuttle (e.g., local bus, school bus, van pool)
    e. On rail transportation (e.g., Green line, Blue line, NorthStar Commuter Rail, Amtrak)
    f. Walked, jogged, or rolled using a mobility device such as a wheelchair
    g. On a bicycle
    h. On a scooter, moped, or similar device
    i. None of the above (*EXCLUSIVE OPTION*)
17. *(If Q13 == a, b, c, f, g)* Assuming that your employer allowed you to work from home, how often would you choose to work from home?
    a. 5+ days a week
    b. 3-4 days a week
    c. 1-2 days a week
    d. Less than 1 day a week
    e. Never

The following question asks about any changes to your past employment situation and any changes that may have occurred during the pandemic.

18. Which of the following (if any) has happened to you during the COVID-19 Outbreak? (Select all that apply)
    a. Permanently laid-off
    b. Left job (quit) by choice or necessity
    c. Temporarily furloughed **with** pay
    d. Temporarily furloughed **without** pay
    e. Work hours reduced
    f. Pay-cut
    g. Pay increased
    h. Pay structure changed (e.g., different incentives, bonus, benefits)
    i. None of the above *(EXCLUSIVE OPTION)*

The following questions are related to your life prior to **March 2020**. This is when Minnesota began implementing stay-at-home orders and other public health measures.

19. What was your employment status before **March 2020** (Select which best describes you)
    a. Employed Full Time
    b. Employed Part Time
    c. Unemployed Looking for Work
    d. Unemployed Not Looking for Work

e. Retired
f. Primarily Self-Employed
g. Unpaid Volunteer or Intern
h. Homemaker or Stay at Home

20. *(If Q19 == a, b, f, g)* Before **March 2020**, which of the following best describes your **past** work location?
    a. Work ONLY from home (self-employed or only telework)
    b. Telework some days and travel to a work location for the remainder
    c. Only one work location (outside of home)
    d. Work location is outside of home and regularly varies (different offices/job sites)
    e. Drive/bike/travel for work (driver, sales, deliveries)
21. *(If Q20 != a)* Before **March 2020**, what travel option did you typically take to work? (Select all that apply)
    a. In a household vehicle (or motorcycle)
    b. In another vehicle (e.g., rental, carshare, friend's vehicle, work vehicle)
    c. In a taxi or ride service (e.g., Uber, Lyft)
    d. In a bus or shuttle (e.g., local bus, school bus, van pool)
    e. On rail transportation (e.g., Green line, Blue line, NorthStar Commuter Rail, Amtrak)
    f. Walked, jogged, or rolled using a mobility device such as a wheelchair
    g. On a bicycle
    h. On a scooter, moped, or similar device
    i. None of the above (*EXCLUSIVE OPTION*)
    j. I did not commute to work *(EXCLUSIVE OPTION)*
22. *(If Q19 == a, b, c, f, g)* Before **March 2020**, how often did you typically work from home or telework (instead of going to work that day)
    a. 5+ days a week
    b. 3-4 days a week
    c. 1-2 days a week
    d. Less than 1 day a week
    e. Never

Section 4: Household Information

23. Who lives in your household with you? (please check all that apply)
    a. No one *(Exclusive Option)*
    b. Spouse / Partner
    c. Children under 6
    d. Children aged 6-17
    e. Children aged 18 or older
    f. Roommates(s)
    g. Parents
    h. Other *(Free text option)*
24. In 2019, what was your household's total annual income (from all sources before taxes/deductions from pay)?
    a. Less than $25,000

b. $25,000 - $49,999
c. $50,000 - $74,999
d. $75,000 - $99,999
e. $100,000 - $124,999
f. $125,000 - $199,999
g. $200,00 or more

25. How long have you lived in your current home?
    a. Moved in after March 2020
    b. Less than 2 Years
    c. 2-4 Years
    d. 5-9 Years
    e. 10+ Years
26. What type of place is your current residence?
    a. Single Family House
    b. Townhouse
    c. Building with 2-4 Units
    d. Building with 5 or more apartments or condos
    e. Senior or age-restricted apartments or condos
    f. Dorm, group quarters, or institutional facility
    g. Manufactured home / Mobile Home / Trailer
    h. Other *(Free Text Response)*
27. Do you own or rent your current home?
    a. Own
    b. Rent
    c. Other *(Free Text Response)*
28. How long do you intend to stay in your current home?
    a. Less than one year
    b. 1-4 Years
    c. 5-9 Years
    d. 10+ Years

Section 5: Transportation Questions

29. How many licensed drivers are there in your household?
    a. *Numeric (0-10)*
30. How many working vehicles (including cars, pickup trucks, SUVs and vans) are there available to your household.
    a. *Numeric (0-10)*
31. *(If Q30 !=0)* How large is the burden of owning, driving, and maintaining your car?
    a. No burden at all
    b. A small burden
    c. Something of a burden
    d. A large burden
32. Prior to March 2020, which of the following modes were you willing to consider using for your daily transportation? (Check all that apply)

a. Personal Vehicle
b. Carpool
c. Cab / Taxi
d. Uber / Lyft / Ride Share
e. Public Transit (Bus, Light Rail, etc.)
f. Park and Ride
g. Biking
h. Walking

33. Since March 2020, which of the following modes are you willing to consider using for daily transportation? (Check all that apply)
    a. Personal Vehicle
    b. Carpool
    c. Cab / Taxi
    d. Uber / Lyft / Ride Share
    e. Public Transit (Bus, Light Rail, etc.)
    f. Park and Ride
    g. Biking
    h. Walking
34. Have you ever taken **public transportation** before? *Select All Question*
    a. No, I have not *(Exclusive Option)*
    b. Yes, I have taken regular buses
    c. Yes, I have taken bus rapid transit (A line, C Line, Red Line, etc.)
    d. Yes, I have taken light rail and or commuter rail
    e. Yes, I have done park and ride
35. On your commute, how often do you make stops, such as to drop children off at school or go to the store?
    a. Never
    b. Sometimes
    c. About half the time
    d. Most of the time
    e. Always

The following questions are related to your comfort level using public transit services and your interest in increasing your usage of public transit services.

36. Prior to **March 2020**, how interested were you in increasing your usage of public transit services?
    a. Not interested
    b. Slightly interested
    c. Interested
    d. Very interested
37. Prior to **March 2020**, how comfortably were you in using public transit services
    a. Not comfortable
    b. Slightly comfortable
    c. Comfortable

    d. Very comfortable
38. **Currently**, how interested are you in increasing your usage of public transit services?
    a. Not interested
    b. Slightly interested
    c. Interested
    d. Very interested
39. **Currently**, how comfortable are you in using public transit services?
    a. Not comfortable
    b. Slightly comfortable
    c. Comfortable
    d. Very comfortable
40. What improvements could be made to **current** public transit services that would increase your **interest** in using them? (Select all that apply)
    a. Closer stops to home and/or destination
    b. Safer or more pleasant walking routes to stops
    c. More amenities (shelters, heat, light) at stops stations or waiting areas
    d. More comfortable buses/trains
    e. Faster travel speeds
    f. Transit advantages like bus-only lanes
    g. More frequent service
    h. Service starting earlier and/or running later into the evening
    i. Buses or trains that run closer to on time
    j. Better real-time information on when buses and trains will arrive
    k. Lower fare
41. What improvements could be made to **current** public transit services that would make you more **comfortable** using them? (Select all that apply)
    a. Increased cleaning frequency
    b. Enforcing mask requirements more strongly
    c. Presence of ambassadors on board buses and trains
    d. Presence of Metro Transit police on board buses and trains
    e. Limiting seating options to promote social distancing
    f. Contactless payment options
    g. Live video surveillance of buses and trains
    h. Options to text transit control center to report issues with vehicles or passengers
    i. Improved boarding and exiting procedures

Section 6: Coronavirus Questions

42. How concerned are you with contracting Coronavirus?
    a. Not at all concerned
    b. Slightly concerned
    c. Concerned
    d. Very Concerned
43. How concerned are you with your friends and family contracting Coronavirus?
    a. Not at all concerned

b. Slightly concerned
c. Concerned
d. Very Concerned

44. Do you agree with the following statements about how your life has changed because of Coronavirus? (Select all that apply)
    a. I do not leave the house as frequently as I did before Coronavirus
    b. I do not Eat Out as frequently as I did before Coronavirus
    c. I do not engage in Personal Business activities as frequently as I did before Coronavirus
    d. I do not engage in Leisure and Recreation activities as frequently as I did before Coronavirus
    e. I work from home more frequently that before Coronavirus
    f. I engage in trips by myself more frequently that I did before Coronavirus
45. Have you experienced any of these life events **since March 2020**? (Select all that apply)
    a. I have experienced financial hardship because of Coronavirus
    b. I have experienced emotional hardship because of Coronavirus
    c. I have felt isolated at times because of Coronavirus
    d. I have felt that I do not have an adequate support system during the pandemic
    e. None of the above *(Exclusive Option)*

Section 7: General Health Questions

46. How would you evaluate your overall health? Would you say you are:
    a. Poor
    b. Fair
    c. Good
    d. Very Good
    e. Excellent
47. Do you have a disability? This may include difficulties in Hearing, Vision, Cognition, Movement, Self-Care, Independent Living.
    a. Yes
    b. No
    c. Prefer Not to Answer
48. Please indicate if you have a health condition that puts you at an increased risk for sever illness from COVID-19. Some of these health conditions include:
    - Cancer
    - Chronic Kidney Disease
    - COPD
    - Immunocompromised State
    - Obesity
    - Serious Heart Conditions
    - Sickle Cell Disease
    - Type II Diabetes

    a. Yes
    b. No
    c. Prefer not to answer

49. To date, have you been tested for COVID-19?
    a. Yes, Diagnostic Test (Swab)
    b. Yes, for the antibody after having the virus
    c. Yes, for both
    d. No
50. *(If Q49 != d)* Have you tested positive for COVID-19
    a. Yes, for the active virus
    b. Yes, for the antibody after having the virus
    c. Yes, for both
    d. No
    e. Still awaiting results from the test
51. *(If Q49 == d OR Q50 == d)* Even if you have not tested positive, do you believe that you have had COVID-19?
    a. Yes
    b. No
52. *(If Q23 != a)* Has anyone in your household tested positive for COVID-19?
    a. Yes
    b. No
    c. I live alone
53. *(If Q52 == b)* Does anyone who lives with you believe they have had COVID-19, even if they have not tested positive?
    a. Yes
    b. No
    c. Don't know
54. Have you been vaccinated for COVID-19
    a. Yes, 2 Doses
    b. Yes, 1 Dose
    c. No
55. *(If Q54 == No)* Have you had an opportunity to receive a COVID-19 vaccine?
    a. Yes
    b. No
56. How much of a threat, if any, is the coronavirus outbreak for you personal health?
    a. A major threat
    b. A minor threat
    c. Not a threat
57. *(If Q23 != a)* How much of a threat, if any, is the coronavirus outbreak for others in your household?
    a. A major threat
    b. A minor threat
    c. Not a threat

Thank you for completing the survey. You will receive an email from Daynamica Inc. at noreply.daynamica@gmail.com explaining how to download the Daynamica App onto your smartphone. If you have any questions, the study team can be contacted at cti@umn.edu.

Appendix 2: In App Survey

In App Episode Level Survey:

1. How many **contacts** occurred during this (Trip/Activity)?
    a. Options: Sliding scale 1 - 25, 25 is listed as "25+"
    b. Notes:

    Popup around the word Contact:

    "A contact with another individual is defined by at least one of the following criteria being met:

    - Physical Contact
    - In person conversation for at least 30 seconds
    - Being within 6 feet for at least 5 minutes"
2. How many **contacts** occurred during this (Trip/Activity) with individuals you regularly interact with in person?
    a. Options: Sliding scale 1 - 25, 25 is listed as "25+".
    b. Notes:

    Popup around the word Contact:

    "A contact with another individual is defined by at least one of the following criteria being met:

    - Physical Contact
    - In person conversation for at least 30 seconds
    - Being within 6 feet for at least 5 minutes"
3. *(Activity Only)* How **crowded** was the environment of this activity at its peak?
    a. Options: [Not Crowded], [Somewhat Crowded], [Crowded], [Very Crowded]
    b. Notes:

    Popup around the word crowded:

    "This question aims to determine how packed the space of the activity was at its most crowded. For example, a small room with a lot of people would be *Very Crowded* or an activity by yourself would be considered *Not Crowded*."

4. *(Trip Only)* How **congested** was the environment around the trip at its peak?
    a. Options: [Not Congested], [Somewhat Congested], [Congested], [Very Congested]
    b. Notes:

    Popup around the word congested:

"This question aims to determine how packed the space of the trip is at its most congested. For example, a car trip where there was a lot of traffic would be *Very Congested* or a walking trip where you did not encounter traffic would be *Not Congested*.

5. *(Activities not HOME/WORK)* How important do you consider this activity?
    a. Options: [Not at all important] / [Slightly Important] / [Important] / [Very Important] / [Unsure]
6. *If Q5 == [Slightly Important] / [Important] / [Very Important],* What category best fits this activity's purpose (Select all that apply):
    i. Options: [Financial] / [Social] / [Familial] / [Personal] / [Groceries/Shopping] / [Health] / [Caregiving] / [Other]
7. *(Activities not HOME/WORK)* How time sensitive was this activity? Had to be done: (select only one)
    a. Options: [At this time] / [Around this time] / [Today] / [This week] / [This month] / This was not a time sensitive activity]
8. Please indicate how much you agree with the following statement: For this *(Trip/Activity)*, I am concerned with my risk of contracting coronavirus.
    a. Options: [Strongly Disagree], [Disagree], [Undecided], [Agree], [Strongly Agree]
9. *(Shopping, Personal Business, Leisure & Recreation, Eat Out Activities Only)* What percentage of your time was spent inside/outside during this activity?
    a. Options: Sliding scale (0-1) for Inside vs Outside

       [0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, 100%]
    b. Inside Half and Half Outside

       |---x---------|

10. *(Shopping)* Which categories best describe the purpose of the shopping activity: (Select all that apply)
    a. Takeout Food
    b. Groceries
    c. Clothing
    d. Household Supplies
    e. Other Essential Items
    f. Non-Essential Items
11. *(All Trips)* Select what applies to this trip:
    a. Options: [I used my preferred mode] / [I would have preferred using a different mode]
12. *(If Q11 == "I would have preferred using a different mode")* Which of the following is your preferred mode of transportation for this trip?
    a. Options: [Drive alone] / [Carpool] / [Transit] / [Park and Ride] / [Bike] / [Walk] / [Ride hail] / [Other]
13. *(All Trips)* Would you have used this transportation mode before Coronavirus?

    a. Options: [Yes] / [No]

14. *(If Q13 == "No")*: Which mode would you have likely used for this trip before COVID (Select all that apply):
    a. [Drive alone] / [Carpool] / [Transit] / [Park and Ride] / [Bike] / [Walk] / [Ride hail] / [Other]
15. *(Trips that contain a car segment)* Would you ever consider using public transportation for this trip?
    a. Options: [Yes] / [No]
16. Would you be willing to answer 8 additional questions related to your mood for this *(Trip/Activity)*?
    a. Options: [Yes] / [No]
17. *(If Q16 == "Yes")* (All Activities and Trips) on a scale of 0-6, with 0 as the least and 6 as the most:
    a. How **happy** did you feel during this (Trip/Activity)
    b. How **tired** did you feel during this (Trip/Activity)
    c. How **stressed** did you feel during this (Trip/Activity)
    d. How **sad** did you feel during this (Trip/Activity)
    e. How much **pain** did you feel during this (Trip/Activity), if any?
    f. How **meaningful** did you consider what you were doing?
    g. How **lonely** did you feel during this (Trip/Activity)
    h. How **safe** did you feel during this (Trip/Activity)

In App End of Day Survey:

1. Were there any activities that you wanted to do today but chose not to for COVID19 related reasons?
    a. Options: [Yes] / [No] / [Unsure]
2. *(If Q1 == "Yes")* What type of activities (Select all that apply):
    a. Options: [Shopping] / [Eat Out] / [Personal Business] / [Leisure & Recreation] / [Work] / [Education] / [Other]
3. *(If Q1 == "Yes")* How much time did you spend at home instead of engaging in these activities: How much time would these activities have lasted for.
    a. Options: [Less than 1 Hour] / [1-2 hours] / [3-6 hours] / [Greater than 6 hours]
4. (*If Q1 == "Yes")* What were the reasons the activity was cancelled (Select all that apply):
    a. Options: [The activity was not possible because of lockdowns and other restrictions] / [I did not want to risk exposing myself or others to Coronavirus] / [I now have other obligations which prevent me from engaging in the activity] / [Other reasons]
5. Did limited transportation options and or lack of transportation options prevent you from engaging in specific activities today?
    a. Options: [Yes] / [No]
6. *(If Q5 == "Yes")* What type of activities (Select all that apply):
        i. Options: [Shopping] / [Eat Out] / [Personal Business] / [Leisure & Recreation] / [Work] / [Education] / [Other]

7. Indicate how much you agree with the following statement: Overall, I am concerned with having contracted Coronavirus today. (Select one):
    a. Options: [Strongly Agree] / [Agree] / [Unsure] / [Disagree] / [Strongly Disagree]
8. Did you work from home on this day?
    a. Options: [Yes] / [No]
9. *(If Q8 == "Yes")*How many hours did you work?
    a. Options: [0-1] / [1-4] / [4-8] / [8+]
10. *(If Q8 == "Yes")* Did you work from home because of Coronavirus?
    a. Options: [Yes] / [No]
11. Did you engage in any online shopping today?
    a. Options: [Yes] / [No]
12. *(If Q11 == "Yes")* Would some of this shopping have been done at physical retail stores prior to Coronavirus?
    a. Options: [Yes] / [No] / [Unsure]
13. *(If Q12 == "Yes")* What category does the shopping fit into: (Select all that apply)
    a. Options: [Prepared Food] / [Groceries] / [Clothing] / [Household Supplies] / [Other Essential Items] / [Non-Essential Items]
14. Did you have anything delivered to your house today?
    a. Options: [Yes] / [No]
15. *(If Q14 == "Yes")* Would this delivery have occurred prior to Coronavirus
    a. Options: [Yes] / [No]
16. *(If Q14 == "Yes")* What category does the delivery(s) fit into: (Select all that apply)
    a. Options: [Takeout Food] / [Groceries] / [Clothing] / [Household Supplies] / [Other Essential Items] / [Non-Essential Items]
17. Did you utilize services like In-Store Pickup/Curbside Pickup/Drive through to shop today?
    a. Options: [Yes] / [No]
18. *(If Q17 == "Yes")* Would this have been the preferred mode prior to Coronavirus
    a. Options: [Yes] / [No]
19. *(If Q18 == "Yes")* What would have been the preferred method of shopping prior?
    a. Options: [Online Shopping with Delivery] / [Shopping in Store] / [Other Method]
20. *(If Q18 == "Yes")* What category does your shopping activity fit into: (Select all that apply)
    a. Options: [Prepared Food] / [Groceries] / [Clothing] / [Household Supplies] / [Other Essential Items] / [Non-Essential Items]