INCENTIVIZING ACTIVE AND SHARED TRAVEL PILOT PROGRAM

Final Report - Final

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METROPOLITAN TRANSPORTATION COMMISSION

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EXECUTIVE SUMMARY

The Metropolitan Transportation Commission's (MTC) Climate Initiatives Program, as part of Plan Bay Area 2050 (PBA 2050), aims to reduce greenhouse gas emissions by reducing vehicle miles traveled (VMT). The Incentivizing Active and Shared Travel Pilot Program ("Pilot") utilized behavioral economics and experimentation to achieve the goals of PBA 2050 by understanding traveler behavior and promoting sustainable mobility options.

The Pilot was initiated in May 2021 with the goal of understanding travel behavior in the post-COVID era. However, the project encountered unforeseen challenges due to the unexpected surge in COVID-19 cases throughout the remainder of 2021. This surge led to most companies implementing work-from-home policies, which significantly disrupted the planned execution of the project. Additionally, the prolonged pandemic had a potential impact on the recruitment prospects, which put the successful completion of the project at considerable risk. In response to these risks, MTC and the research team explored adjustments to the research methods and data collection approach, seeking to adapt to the prevailing circumstances. As a result, the research team successfully recruited 200+ participants and kept the participant retention expenses within the budget.

The Pilot focused on identifying drivers open to behavior change (nudgeable drivers) and evaluating interventions to achieve shifts in travel choices towards sustainable modes. It recognized that not all travelers are suitable targets for behavior change campaigns and the most effective approach used personalization to shift trips rather than a blanket approach that does not take into consideration if the mode is feasible for the participant.

The GoEzy mobile app was the primary mobility platform and app for executing the experiment design, that included onboarding, coaching, delivering monetary and non-monetary interventions, and collecting data. The quantitative and qualitative data analysis collected through GoEzy, combined with separately collected socio-demographics, activity characteristics, and transportation constraint data helped to illuminate users' preferred modes and their underlying reasons for travel behaviors.

The overall experiment results are summarized below:

1. **Characteristics of nudgeable drivers**:
    - ***Are older working-age adults***. Older participating drivers, particularly those between the ages of 37 and 56, were more receptive to the behavioral interventions and nudges aimed at promoting sustainable transportation choices relative to younger drivers in the study. This age group might be more open to considering behavior changes and adopting new travel modes.
    - ***Have multiple mode options***. Participating drivers who had access to and were familiar with multiple transportation options were more likely to respond positively to the interventions. Having various mode choices might make them more willing to explore alternative options.
    - ***Own a bicycle***. Participating drivers who own a bicycle were more likely to positively respond to the interventions. This suggests that these individuals may comprehend the practical advantages of using alternative transportation modes when they already have a bike. Owning

a bike is a lifestyle choice, and, consequently, these individuals may also self-identify with sustainability, making them inclined to use non-driving modes when nudges are present.

- ***Residents from certain regions exhibited pronounced responsiveness to interventions***. There was a marked response in San Francisco County, particularly in the zip codes of 94122 and 94118. In Contra Costa County, cities like Danville (94526) and Antioch (94509) showed notable receptiveness. Within Santa Clara County, areas such as Palo Alto (94303), Los Altos (94024 and 94022), San Jose (95123 and 95132), and Campbell (95008) also registered increased responsiveness. However, further research is needed to understand why these locations were most receptive to the experiments.

2. **Travel patterns of nudgeable trips**:
    - ***Shorter travel time and distance***. Participating drivers showed greater responsiveness to incentives for trips of shorter travel durations and distances. This suggests that promoting active and shared modes for shorter trips might be more effective in encouraging behavior change.
    - ***More likely to switch to walking for trips less than 3 miles***. Participating drivers were more willing to switch to walking as a mode of transportation for trips that were less than 3 miles. Walking was perceived as a feasible and convenient option for short-distance trips.
    - ***More likely to switch to cycling for trips less than 10 miles***. Similar to walking, cycling was favored as a mode of transportation for trips that were less than 10 miles. Participating drivers might view cycling as a viable option for covering moderate distances.
    - ***Weekday trips show higher responsiveness to nudges than weekends***. Nudges and interventions were more effective in influencing travel behavior during weekdays compared to weekends. Weekday trips might involve regular commuting patterns, making participating drivers more receptive to behavior changes.
3. **Effects of different messaging strategies**:
    - ***A blanket "Public Transit" message had no significant effect on mode adoption***. Simply providing information about public transit options without considering access, transfer times, and in-vehicle times did not result in significant changes in mode adoption. However, participating drivers were more likely to switch to transit when the option had a short walk to access the services (up to 16 minutes) and short in-vehicle times (up to 21 minutes) and an incentive was offered. Incentives helped overcome initial resistance or hesitation, providing the necessary motivation to make the switch – see the next section, “Effects of Incentives” for more information.
    - ***"Do Not Drive" message increased non-driving mode adoption, especially cycling***. Encouraging participating drivers to avoid driving for certain trips had a positive impact on promoting non-driving modes, with cycling being one of the preferred options.
    - ***Flexible travelers are more receptive to non-driving options***. Those experienced with active and shared travel modes are open to message interventions and can be considered “nudgeable drivers.”

4. **Effects of incentives**:
    - ***Offering a $3-$5 incentive increased usage of multiple modes for a given trip***. Providing monetary rewards in the range of $3 to $5 was effective in encouraging participating drivers to use intermodal transportation options (i.e., incorporating transit and walking when using other modes like cars or bike) for their trips.
    - ***Lower rewards were needed when presenting the second-best [1] option compared to random suggestions***. In the case of a habitual trip, if participating drivers are presented with a feasible alternative mode option (the second-best choice) instead of a random recommendation that may or may not work for that specific trip, a smaller incentive is required. This is intuitively clear because the second-best option is the most appealing choice after driving. When offering such appealing modes, it naturally requires fewer incentives for drivers to switch.
    - ***Suggestions to walk or cycle that included rewards increased non-driving mode adoption***. Offering rewards for suggested walking and cycling trips positively influenced participants to choose non-driving modes versus providing the same suggestion without rewards. This was true regardless of whether walking or cycling was the second-best travel option.
    - ***Suggestions to use transit that included rewards increased non-driving mode adoption if transit was the second-best option***. Participants were more likely to switch to transit when it was their second-best transit option with an incentive compared to when it was the second-best transit option but was suggested without a reward.
    - ***Suggestions to use transit that included rewards had a positive effect on behavior change when the time taken to reach the transit station or stop (access time) was less than 15 minutes***. Offering rewards for using transit when the access time was less than 15 minutes proved effective in promoting public transportation use. This was true regardless of whether transit was the second-best travel option.

These findings provide valuable insights for developing targeted strategies to encourage nudgeable drivers to shift towards more sustainable travel modes and tailoring interventions to specific user characteristics and trip details. The ideas and concepts derived from the findings are also provided to MTC to consider in future transportation demand management (TDM) program strategy development and expansion.

Recommendations

The findings of the Pilot hold significant promise in shaping and inspiring the practical implementation of an innovative Travel Demand Management (TDM) program for MTC. The existence of nudgeable drivers and their identifiable personas and travel patterns offer valuable insights that can enhance the cost-effectiveness of a scaled-up program. A 3-step process is proposed for scale-up implementation, as shown in Figure ES-1 below, with further elaboration provided in the sub-sections.

The suggestions and ideas presented aim to serve as a foundation for future behavior change programs. By capitalizing on the knowledge gained, MTC can develop a more impactful and efficient approach to managing travel demand in the region.

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[1] The second-best option is defined as the most appealing sustainable mode option next to driving for a particular origin-destination for a specific participating driver. The second-best option is highly personalized.

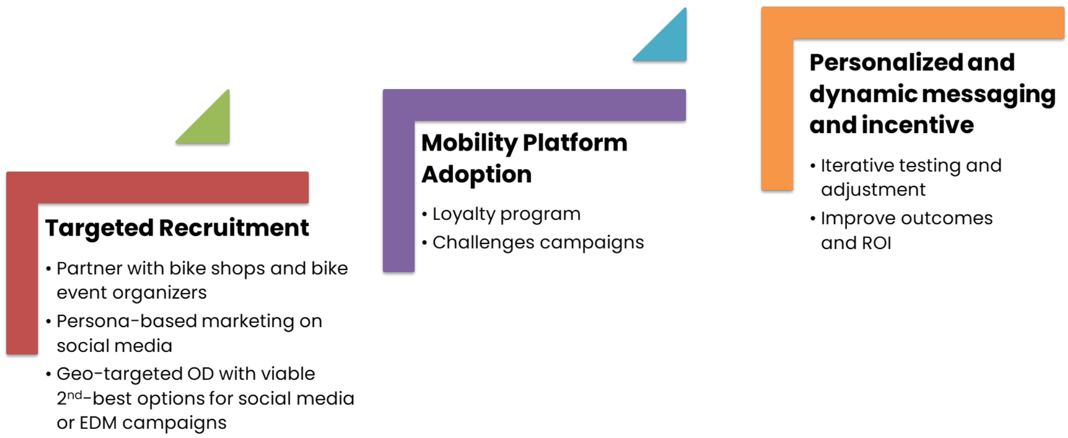


Figure ES-1: Scale-up Approach

1. Targeted Recruitment

The Pilot identified nudgeable drivers, and reaching out to them for future campaigns is a crucial first step in the scale-up program. To achieve this, we recommend exploring various approaches, including implementing persona-based marketing strategies on social media platforms that can help target specific audience segments similar to the personas identified in this study. Tailoring messaging and content to resonate with different user groups can help to address their unique transportation needs effectively.

> Nudgeable drivers exist. Reaching out to them and inviting them to participate in future campaigns is an important first step.

Additionally, MTC can use geo-targeting techniques to identify and engage potential users within specific Origin-Destination (OD) pairs that offer appealing second-best options. Using OD trip matrices from MTC's travel demand model can identify OD pairs with high trip volumes, shorter distances, and attractive second-best options as the targeted recruitment areas. This process can be executed similarly to the Mobility Option Discovery process employed in this study, ensuring effective and strategic recruitment of potential users.

Lastly, we recommend diversifying outreach or marketing approaches that can help to invite more participants into future campaigns. In addition to social media, partnerships can be considered, such as collaborating with local bike shops and bike event organizers to promote TDM campaigns on the mobility platform. Joint marketing efforts could involve offering exclusive discounts or incentives to customers who participate in the campaigns or adopt the platform.

2. Mobility Platform Adoption

A mobility platform enhances engagement, and targeted outreach can be effective in improving campaign outcomes.

A mobility platform is a desirable tool to onboard, retain, coach, educate, and deliver personalized messages and incentive campaigns. Using the mobility platform and a mobile app is common in the areas of fitness and health, education and language learning, personal finance, etc. In those areas, mobile apps play a crucial role in engaging and guiding users through onboarding and coaching processes, contributing to enhanced user experiences and successful outcomes.

However, if MTC decides not to implement a mobility platform, collecting data and engaging users are feasible, but it becomes more difficult to understand user movement and activity patterns and to track responses and effectiveness. Traditional methods such as mobile web-based activity recall and logging can be employed to track and record user activities. In this approach, users are prompted to manually record their daily activities. However, this method has drawbacks, including the heavy workload it imposes on users and the potential for inaccuracies in recalling past activities.

3. Personalized and Dynamic Nudges

Delivering personalized behavioral nudging to the nudgeable drivers and continue learning and improving for the scale-up program.

Regarding the communication approach, an alternative method could involve using electronic surveys, SMS tracking, or QR code feedback systems at physical locations. Regular email reminders or phone notifications can also be utilized to keep users informed about specific triggers or actions.

In industries where mobile apps are commonly used for onboarding and coaching users, various behavior techniques are employed to enhance engagement and motivation. These techniques include personalization, gamification, goal setting, positive reinforcement, social interaction, behavioral prompts, and feedback visualization.

Targeted messaging encouraging walking for short trips under 3 miles and biking for trips between 3 and 10 miles presents a promising opportunity for behavior change in urban areas, where short trips are frequent and non-driving options are competitive.

The analysis also revealed that the attractiveness and competitiveness of the second-best mobility option significantly influenced individuals' willingness to adopt active or shared transportation. By targeting resources towards nudgeable individuals who are already inclined to consider sustainable options, interventions can be more effective and cost-efficient.

The adoption of the mobility platform would enable providing personalized trip planning and mode choice recommendations. These recommendations can consider users' profile information, preferences, and available transportation options, leading to more targeted messaging and nudging towards sustainable choices.

While many app-based companies have effectively scaled personalized messaging, it's essential for MTC to assess their unique capabilities and context thoroughly. By focusing on personalization and leveraging their existing investments, MTC can make the most of their resources and intensify the impact of their behavior change campaigns.

1 INTRODUCTION

1.1 Project Background and Objectives

The Metropolitan Transportation Commission's (MTC) Climate Initiatives Program, as identified in Plan Bay Area 2050, invests in strategies to reduce greenhouse gas (GHG) emissions by targeting the reduction of vehicle miles traveled (VMT) in the San Francisco Bay Area. Plan Bay Area 2050 is a long-range plan that addresses key issues such as the economy, environment, housing, and transportation, with the objective of reducing VMT through promoting active and shared transportation options, including walking, biking, transit, and carsharing.

However, simply providing travelers with mobility options and choices does not guarantee immediate or substantial behavior change. If it were that easy, existing trip-planning apps would have already resulted in significant adoption of sustainable modes of transportation. Previous research has shown that habitual behavior strongly influences humans, and once a habit is formed, it takes significant effort to trigger a new behavior. According to Dr. BJ Fogg's Motivation Theory at Stanford University, making change easy increases the likelihood of high and low-motivation travelers engaging in new behaviors (Fogg, 2009). What is often missing is the active presentation of mobility options and meaningful engagement with travelers through appropriate means, such as gamification and incentives, to stimulate desired behavior changes.

Incentive-based Active Demand Management (ADM) programs have explored managing congestion by influencing commuters' decisions to adopt more sustainable mobility choices. Using incentives or rewards to motivate travel behavior change is a well-established and effective strategy. Tailoring rewards to the characteristics of the traveler or trip can lead to lasting behavior change. Therefore, rewards should be diverse, provide value to the user, and be appropriately sized to achieve the desired behavior change. Research suggests that while monetary or material rewards may initially motivate change, they may not ensure long-lasting or permanent behavior change. Rewards may call for taking a specific action so that users know what they are being rewarded for, or they may be randomized (gamified) to encourage continued participation and engagement, which are critical to promoting more sustainable travel habits (Eyal and Far, 2018). Most studies have applied simple incentive schemes based on little knowledge of what motivates the participant and the minimum reward that commuters are willing to accept to give up driving alone during peak times.

MTC’s Incentivizing Active and Shared Travel Pilot Program (“Pilot”), a Climate Initiatives strategy, applied the latest behavioral economics theories and practices to explore effective strategies to trigger and sustain behavior change that reduce VMT and GHGs. The Pilot sought to understand behavior and the tradeoffs between driving in a single occupancy vehicle (SOV) and utilizing a sustainable mobility option (e.g., public transit, biking, etc.) for any type of habitual trip, including shopping, medical/dental, gym, work, etc. By analyzing the tradeoffs SOV users make when presented with other mobility choices, along with incentives, the Pilot aimed to identify how to sustain changes in travel behavior using approaches that can be scaled across the San Francisco Bay Area.

1.2 COVID Travel Pattern Disruption

This study was first planned prior to the COVID-19 pandemic, which created significant disruptions in long-standing patterns of regional travel and presented both a challenge and an opportunity for the project team. The lower levels of overall travel may have dampened interest in or qualification for participation in the Pilot compared to pre-pandemic levels. However, the disruptions in travel habits also present an opportunity to change travel behavior in an enduring way. To that extent, behavior change interventions could help break travel habits that have negative externalities such as driving alone and help to form new travel habits that are active and less polluting. The following sections provide survey highlights and anecdotal evidence pertaining to expected post-COVID mode usage and trip purposes as context for later sections of this report which discuss the Pilot outcomes and research findings.

1.2.1 Car Use Has Largely Rebounded and is Expected to Increase

Based on an online survey conducted in 2020, travel during the early part of the COVID-19 pandemic saw a significant move from public to private transportation and non-motorized modes. The survey also revealed that shopping became the primary purpose of car trips (Abdullah et al., 2020) and working from home decreased commute trips. In July 2020, KPMG estimated that some of the pandemic-related changes in commuting and shopping patterns could be permanent, potentially leading to fewer overall car trips and as much as a 10% reduction in VMT (Siberg et al., 2020). However, data from the Bureau of Transportation Statistics shows that this reduction did not take hold across the entire economy: total VMT at the national level had surpassed 2019 levels by early 2022. (USDOT, 2022; U.S. DOE, 2023) .

The recovery of VMT in California is consistent with the national-level trend, although the nine-county Bay Area does show a lag relative to the rest of the state, presumably due to the especially high concentration of office workers who continue to telework relatively more than in other regions. An analysis of data from Caltrans and the California Department of Finance shows that statewide, monthly freeway VMT per capita exceeded 2019 levels in February 2022, and since then it has remained virtually even with 2019 levels. In the Bay Area, freeway VMT per capita in 2022 was still down about 5% relative to 2019 levels. (California Department of Transportation, 2023).

While the total amount of car travel may be roughly the same on a mileage basis, there is significantly less freeway delay than before the pandemic. An analysis of data from Caltrans’ Performance Measurement System (PeMS) congestion monitoring shows that daily vehicle hours of delay, due to congestion in 2022, was 69% of 2019 levels for California as a whole and only 55% of 2019 levels for the nine-county Bay Area (California Department of Transportation, 2023). This suggests that Bay Area drivers are not making as many car trips during peak hours or to the same concentration of locations as they were before the pandemic.

Much of the reduced delay is likely due to fewer workers commuting to physical job sites. As recently as October 2022, Google’s COVID-19 Community Mobility Data indicated that the number of trips to workplaces in San Francisco were 37% lower than before the pandemic, and San Francisco had the lowest level of work-based travel of all 50 metro areas in the dataset (Rezal, 2023). If Bay Area residents are still driving the same number of miles but without making as many trips oriented towards workplace-based commuting, it may be harder to provide high-quality alternatives to driving alone such as public transit, employer shuttles, and vanpools.

Another factor in the return of overall VMT without prior levels of roadway delay could be related to workers moving further away from their job sites without needing to commute to the office as much as before the COVID-19 pandemic. The challenging Bay Area housing market has long been a force in pushing some workers to seek housing in the outer edges of the region and far from their jobs, but the increased availability of teleworking and hybrid office arrangements that surfaced during the pandemic increased the attractiveness of moving out of the urban core and intensified these pre-existing patterns (Boarnet et al., 2021). Some people decided that they can tolerate a longer drive to the office when they commute less often, trading their urban or close-in suburban home for a bigger one in a sparsely populated exurb where destinations like restaurants or stores are further away, and where sustainable modes like transit or biking are unlikely to be as convenient. Despite commuting to the workplace less often, this could actually increase the total amount of driving for these households. While remote work has allowed people to move away from the cities, teleworkers tend to travel quite a bit, with their destinations likely further away than if they were linking trips with time spent at the office. For instance, those working downtown do not need to drive 30 minutes to reach a shopping mall. Additionally, remote workers can squeeze in extra weekday trips to shops, cafes, and clinics, jostling for space with armadas of delivery trucks (Zipper, 2021; Christian Science Monitor, 2021).

1.2.2 Public Transit Ridership is Struggling to Recover

In contrast to the driving rate, public transit has yet to recover pre-pandemic ridership levels. The pandemic has put public transit on a lifeline, with both ridership and fare revenues still materially lower than pre-pandemic levels. This creates a vicious cycle where, without cash, it is difficult to maintain regular service, and without regular service, it is difficult to attract riders and increase fare revenues. If the significant shift from trains and buses to cars is not reversed, this could worsen traffic congestion and threaten the achievement of climate and air quality goals.

As of February 2023, vehicle revenue hours for the seven largest Bay Area transit operators are running anywhere from 54% to 106% of levels from early 2020 while unlinked passenger trips are only 36% to 72% of 2020 levels. Even if additional funding becomes available to fully restore service, rebuilding prior levels of transit ridership is not expected to happen quickly. For example, a December 2022 briefing book from BART showed multiple ridership scenarios, and only the most optimistic scenario achieves pre-pandemic ridership levels in the next ten years (Woodrow, 2022; BART, 2022).

1.2.3 How Trends Influenced Pilot Program Approach

The significant changes in travel patterns and the differences in recovery across these two modes described above suggested the possibility that past understandings of travel preferences and attitudes may no longer apply. Accordingly, the Pilot program began with a survey of Bay Area residents to explore travelers' pre- and post-pandemic preferences when trying to plan their trips and the barriers they encounter when considering the use of different modes. The survey provided a useful baseline for understanding what types of incentives might need to be offered to influence mode choice in the current environment.

After conducting the survey, a series of experiments were designed to promote the use of sustainable modes among Bay Area travelers. This study was initially intended to focus only on habitual trips, but the post-pandemic travel trends indicated that many Bay Area travelers were no longer making the same volume of habitual trips as before the pandemic. Even if the Pilot was successful in recruiting many participants, it was possible that participants would not have enough habitual trips during the Pilot to be able to measure the effect of incentives with acceptable statistical significance. As a result, two experiment modifications were put in place: (1) clearly communicate with the participants the compensation they would receive if they used the app to plan and record their trips. This would increase the number of habitual trips being recorded; (2) additional components were added to the Pilot experiments to test the effects of information-only nudges for participants' non-habitual trips. This helped increase the scope of research findings that could potentially be gleaned from the significant effort to recruit, qualify, and engage with Pilot participants.

This final report provides the findings of the Pilot program. Chapter 2 briefly reviews the transportation-related concerns and barriers for Bay Area residents. Chapter 3 introduces the study approach. Chapter 4 presents highlights of the study results. Chapter 5 discusses implementation considerations. Chapter 6 lists the relevant literature citations and Chapter 7 is the appendix section including various literature summaries and technical details.

2 TRANSPORTATION CONCERNS AND BARRIERS

To gain insights into potential concerns and barriers related to various transportation modes, a survey was conducted with Bay Area residents using Amazon Mechanical Turk (MTurk) and Facebook (FB).[2] MTurk is a crowdsourcing platform that offers various tasks, including completing surveys, while Facebook is a popular social media platform. MTurk and Facebook were chosen because they allow for the quick collection of survey responses. These platforms enable users to share survey links and target specific geographic areas, ensuring that only residents from those areas can access the survey.

For both platforms, a survey link and request to participate were created and shared with participants in California. Participants were asked to provide their zip code to ensure a representative sample from the Bay Area.

The survey approach was immersive, prompting respondents to consider their most frequently taken trips and provide information about their top three most frequent trips. For each of these trips, respondents answered questions about trip characteristics, their preferences for mobility options (including the best and second-best options), and the barriers they faced in shifting modes of transportation. This approach aimed to capture the most common trips that reflect respondents' daily travel behavior and gather insights into their lifestyle and perceptions of different modes.

In addition to travel patterns, the survey also collected information on other travel-related attributes, such as personal vehicle and cycle availability, frequency of mask-wearing, vaccination status, and socio-demographic factors.

2.1 Survey Questionnaire

The survey sections and question content are outlined below. The first three sections of the survey asked respondents to think about their top three most frequent trips and then answer questions about each of these trips, while the last section asked respondents to provide information on other pertinent travel and socio-demographic characteristics. Appendix 7.6 includes the initial qualification survey and the full survey questionnaire.

Section 1: Trip characteristics: Questions asked about the purpose of the trip, the frequency of the trip, what time of day and day of week the trip takes place, the level of flexibility in terms of departure time (leave early or late), if the respondent takes the trip alone or with others, and how long the trip takes.

Section 2: Mobility options preference: Questions asked about the best and the second-best mobility option for each trip based on their experiences and preferences before and after the pandemic. The set of mobility options provided to the respondents included:

- ***Personal Vehicle***: Drive alone.
- ***Carpool***: Traveling in your or other vehicle with 1-3 other people.
- ***Vanpool***: Traveling in a van with colleagues or classmates within the same organization, most likely provided by your employer.

[2] Survey conducted from September 15 to October 6, 2021.

- ***Rideshare services***: Such as Uber, Lyft and/or their shared services Uber Pool, Lyft Line.
- ***Carshare***: Rent a car or borrow someone else's car.
- ***Public Transit***: Such as BART or bus.
- ***Micromobility***: Walk, cycle, scooter, or other shared modes.

Section 3: Barriers towards mode shift: Questions asked the respondents to list all the reasons why they do not use each of the mobility options identified in the previous set of questions. Unsatisfactory accessibility, unsatisfactory reliability, unsatisfactory safety, unsatisfactory health risk, unsatisfactory comfort, unsatisfactory cost, and unfamiliarity are among the barriers provided to the respondents. A description of each barrier is also provided to the respondents along with the option to choose if they believe there is no barrier to them choosing a certain mobility option. The list below provides a description of each barrier:

- ***Accessibility***: How easy it is to access this mode, including whether you have access to it, and if the entire journey duration, walking distance, and other factors are acceptable.
- ***Reliability***: Refers to the perception of the respondent if the mode selected runs on time.
- ***Safety***: Any perceived personal or road safety related risk when using the selected mode.
- ***Health risk***: Any perceived health risk when using the selected mode.
- ***Comfort***: Comfort level of the selected mode.
- ***Cost***: How satisfied is the respondent with the fare, parking cost, etc.
- ***Familiarity***: Familiarity of the respondent with the mode.

Section 4: **Other pertinent travel and socio-demographic characteristics**.

- ***Personal vehicle and cycle availability***: Respondents were asked how often they use their personal vehicle and about bicycle availability. In addition, respondents were asked how many personal vehicles their household owns.
- ***Mask wearing and vaccination***: Respondents were asked how often they wear masks in a public indoor environment and whether they have been vaccinated.
- ***Socio-demographics***: Respondents were asked general information that could be associated with their level of generating demand for travel such as age, number of children under 18, and household income.
- ***Location***: Respondents were asked about their home and work zip codes to filter out responses not from the Bay Area.

2.2 Basic Descriptive Statistics

Most Frequent Trips and Trip Purpose

Respondents were asked to recall their three most frequent trips and identify the purpose and frequency of those trips. Figure 2-1 illustrates the frequency distribution of these trips for each of the trip purposes identified below.

- Commuting (work or school)
- Pick-up/drop-off (family members or friends)

- Grocery/shopping
- Dining
- Leisure (e.g., exercise, sporting event, outdoor activities)
- Social (visit friends/family)
- Community/Volunteering or Religious Event
- Personal Business/Errands (medical/dental, bank, post office, etc.)
- Other_______

Figure 2-1 shows the percentage of respondents who mentioned the trip purpose as one of their most frequent trips. For example, 63 percent of the respondents selected grocery shopping as one of their most frequent trips. The percentage within each trip purpose represents the distribution of the frequency of that trip purpose. They were normalized to make the percentages within each trip purpose equal to one. For example, among the respondents who selected grocery shopping as one of their most frequent trips, over 60 percent of those make this type of trip 1-3 times a week. Commuting and grocery shopping were the most common among respondents. Commuting was identified by 58 percent of the respondents as their most frequent trip, with about 70 percent of those making the trip 4 to 6 times each week. Leisure, errands, and social trips were also often identified, with most respondents indicating that they make the trips 1-3 times per month or 1-3 times per week. While only 29 percent of respondents chose the pickup/drop-off trip as one of their most frequent trips, its frequency distribution is similar to the results for commuting trips.

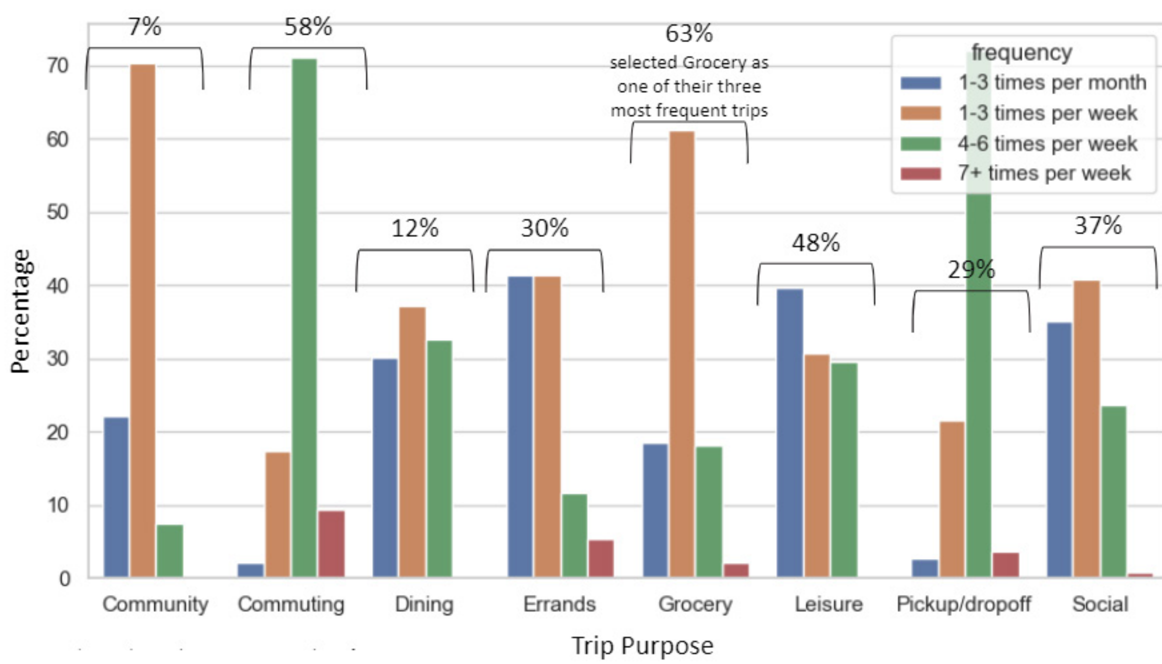


Figure 2-1: Frequency Distribution of the Three Most Frequent Trips by Trip Purpose

Best Mode Option Before COVID-19 and Current Intention

For the top three most frequent trips, a comparison was made between the current best mobility options and the options used before the COVID-19 pandemic. This comparison is illustrated in Figure 2-2.

In the upper half of the circle, the distribution of the current best mobility options is represented by various colors of the ring. In the bottom half of the circle, the distribution of the best mobility options before the pandemic is shown using different colors of the ring.

To provide an example, consider the comparison between the percentage of personal vehicle usage before COVID-19 (represented by the yellow arc at the bottom) and the current percentage (represented by the blue arc at the top). The data shows an increase of 12 percent in personal vehicle usage, from 55 percent before the pandemic to 67 percent in the current situation. The directional links between the lower half of the circle (Before Pandemic) and the upper half of the circle (During Pandemic) represent the proportion of respondents who either changed or maintained their pre-pandemic best mobility option. The colors of the directional links correspond to the pre-pandemic mode choice.

To illustrate, the percentage of respondents who used public transportation both before and during the pandemic decreased by half. This change is depicted by the green directional link stemming out from the lower half Public Transit green ring and pointing towards the upper half Personal Vehicle ring, indicating a significant proportion of respondents who shifted to private cars as their preferred mode of transportation.

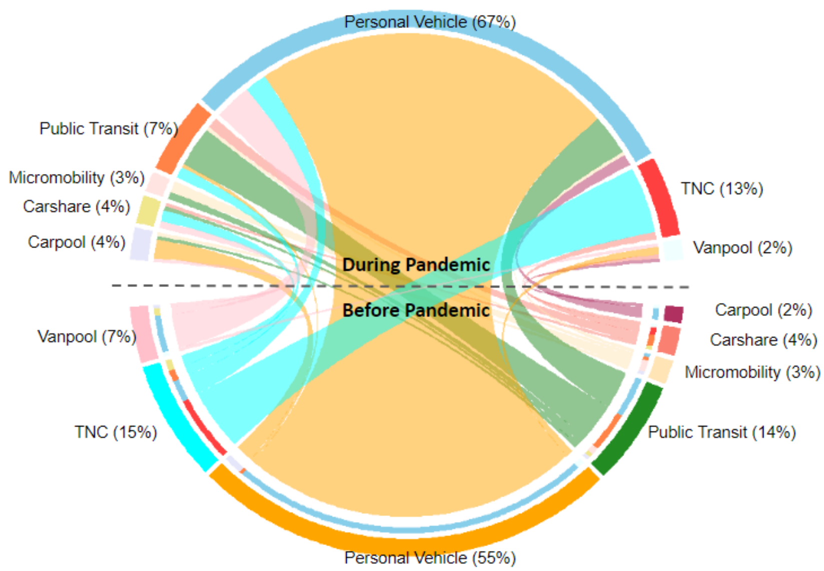


Figure 2-2: Best Mobility Option Before and After Pandemic

In a similar manner, the survey also asked about the second-best mobility option for the subset of respondents whose best option is a personal vehicle, and the distribution of responses is depicted in Figure 2-3.

In the circle diagram, the response "None" indicates that the respondents did not consider any mode other than a personal vehicle as their second-best mobility option, both before and during the pandemic. The directional links from the lower half of the circle to the upper "None" portion of the circle indicate that many people who had a second-best mobility option before the pandemic no longer consider any other option, leading to an increase in the proportion of personal vehicle usage from 23 percent to 38 percent.

While most shared services experienced a decline in usage due to the pandemic, carpooling, public transit, and ridesharing remained popular second-best options. Approximately 15 percent of respondents identified carpooling, 9 percent identified public transit, and 13 percent identified ridesharing as their second-best mobility options.

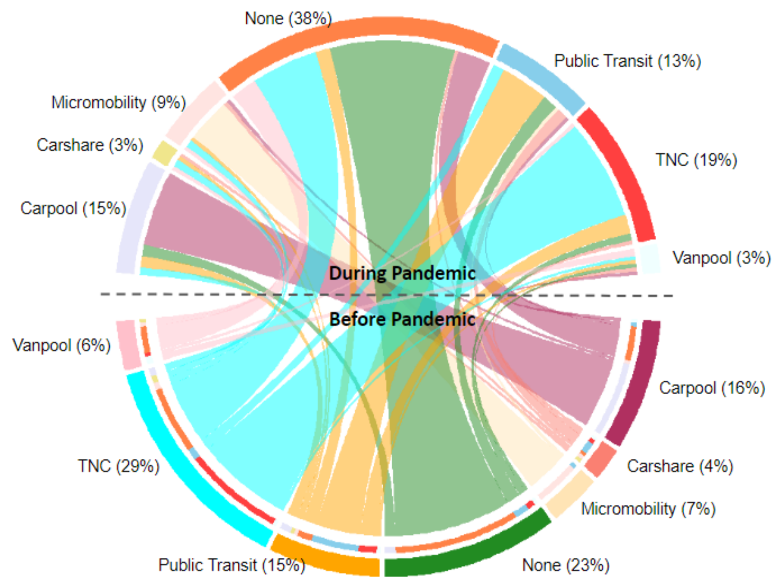


Figure 2-3: Second-Best Mobility Option before COVID-19 and Currently When Best Option is Personal Vehicle

2.3 Behavior Change Barriers

Figure 2-4 illustrates the distribution of barriers that can significantly influence individuals' ability to change their travel behavior. In the diagram, "TNC" refers to rideshare services such as Uber, Lyft, and their shared services like Uber Pool and Lyft Line, while "micromobility" encompasses modes such as walking, personal cycles, scooters, or other shared modes.

For instance, 61.7 percent of the respondents perceived a health risk in using public transit, while 44.3 percent saw a similar risk in using a TNC. On the other hand, 57 percent of the respondents did not perceive any barriers when using their private vehicles.

When examining carpooling, the perceived lack of reliability and accessibility emerged as prominent barriers. This indicated that individuals were concerned about issues like punctuality, potential cancellation of carpool arrangements, unpredictable trip durations, and similar factors.

For vanpooling, the primary barriers identified were unfamiliarity and unsatisfactory accessibility. This is likely due to the limited availability of vanpool services in specific locations, as well as a lack of awareness among individuals about how to utilize such services.

Regarding public transit, dissatisfaction with comfort, reliability, and safety was notable among the identified barriers. These concerns may influence individuals' decisions to choose sustainable modes of transportation.

Lastly, the lack of familiarity stands out as the most significant barrier to adopting micromobility options. Individuals may be hesitant to utilize these modes due to a lack of knowledge or experience with them.

Overall, the distribution of barriers in Figure 2-4 sheds light on the factors that can hinder individuals from changing their travel behavior and highlights the areas where improvements and interventions may be necessary to address these concerns.

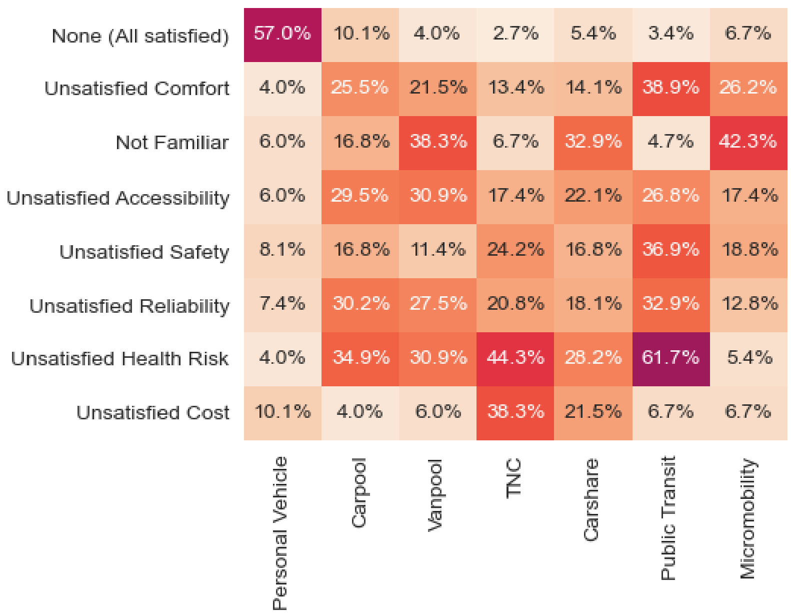


Figure 2-4: Distribution of Barriers by Mobility Options

Knowledge of the barriers individuals face when considering new mobility options is essential in designing effective interventions to increase their motivation to try these options. While identifying barriers was a critical first step, the main challenge was translating this understanding into tangible Pilot interventions. To this extent, this study incorporated the concept of the "second-best" mode option in the intervention design. Consequently, the program aims to present and familiarize individuals with appealing mobility options incrementally to trigger behavior change in a cost-effective manner given these emerged barriers. More details about the experiment design are discussed in Chapter 3.

3 STUDY APPROACH

This chapter outlines the two-pronged research experiment that served as the primary implementation Pilot, which incorporated both monetary and non-monetary interventions aimed at encouraging behavioral change among individuals. Both experiments involved randomized trials and the use of control groups where interventions were not offered, to test the relative differences in key outcomes both with and without the behavioral nudges.

All interventions were delivered to program participants through the use of Metropia's GoEzy app. Before registering for the app, recruited individuals were asked to complete a Google form survey which collected socio-demographic information and details about their existing travel habits, access to non-driving travel modes, and other relevant user data. This information was used to create personas for better understanding the participants.

During the observation period, as recruited individuals used the GoEzy mobile app for their daily trips, their travel patterns were analyzed to identify potential active and shared travel options for these trips. During the experiment period that followed, various monetary and non-monetary interventions were promoted to engage individuals in behavior change.

After briefly describing the difference between the two experimental arms of the Pilot, the subsequent sections of this chapter describe participant recruitment, the overall behavioral design and implementation framework, the specifics of the experimental design, and key details of the GoEzy app that was used at the main platform for the experiments.

3.1 Experiment 1: Targeting Non-Habitual Driving Trips

This experiment focused on non-habitual driving trips, in other words driving trips planned using the GoEzy app where the origin-destination (OD pair)[3] was not flagged as a habitual trip for the user. This experiment evaluated the effectiveness of informational nudges based on behavioral principles, such as the societal cost of driving and green identity. These nudges were designed to encourage active and shared travel usage.

3.2 Experiment 2: Targeting Predicted Upcoming Habitual Driving OD Pairs

In this experiment, predicted upcoming habitual driving OD pairs were targeted. Interventions involved a combination of informative nudges and monetary incentives, which users could redeem for gift cards, to influence participants' mode shift behavior. Rewards were offered in different valuations and combinations to test the sensitivity of outcomes to the specific types of incentives being offered.

3.3 Participant Recruitment

Original Participant Recruitment

Initially, the participant recruitment strategy aimed to onboard a large number of users for the GoEzy

[3] For more details on OD pair identification, please refer to Section 3.4.2.

app. Daily micro incentives were provided for opening the app and utilizing various modes of transportation. The participants were not explicitly informed about their involvement in an experiment. However, in Experiments 1 and 2, messages and incentive treatments were sent to participants based on the experiment designs.

Revised Recruitment Plan Due to COVID

As discussed in Section 1.2, the original recruitment plan needed to be modified due to the impact of COVID-19 which resulted in reluctance in using non-driving modes and decreased commuter activity. To ensure the Pilot achieved a statistically significant amount of trip data, the Pilot was conducted similar to that of a focus group, where participants were informed that the study was commissioned by MTC to understand travel patterns and behavior. Recruitment included a relatively high participation compensation per trip, capped at $5 per week. The execution of the Pilot relied on a comprehensive recruitment plan comprised of six steps designed to identify, engage, and motivate potential users within MTC's nine-county region, as summarized below. All posts and communications were approved by MTC’s communication department. The ultimate success of this process relied on the effective utilization of social media and clear communication with potential users through the MTC project web page and email invitations.

1) Step One: Social Media Outreach

The first step involved posting static and video ads on social media, with a primary focus on Facebook (FB), to reach potential users within the MTC nine-county region. The campaign targeted individuals undertaking at least three weekly trips.

2) Step Two: Project Web Page Engagement

Interested individuals who clicked on the Facebook campaign were directed to a dedicated project web page within the MTC website (Figure 3-1). This page provided comprehensive information about the project's purpose and what participation entailed. Specific details regarding the MTC project web page are outlined in the Task 5.1 memo.

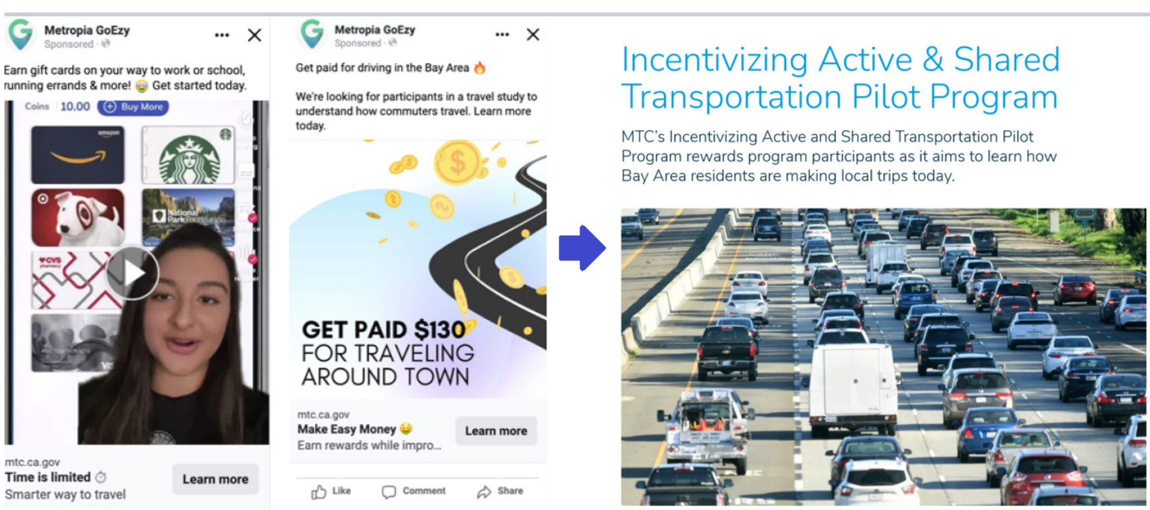


Figure 3-1: Facebook Campaigns and User Recruitment Web Page

3) Step Three: Google Form Qualification

In the third step, interested participants were redirected to a Google form hosted on the MTC project web page. The form served as a qualification tool, by asking respondents to confirm their residency within MTC's nine-county jurisdiction (required) and to provide details about their travel patterns, vehicle availability, views on climate change, and household demographics. After fulfilling these requirements and confirming their residence within the MTC's nine-county jurisdiction, they could then proceed with the sign-up process.

4) Step Four: Daily Invitations

The research team monitored qualified sign-ups daily. Upon identifying a new sign-up, the research team sent out an invitation to download the GoEzy app and register for the Pilot. Each participant received an initial invitation, followed by a maximum of two follow-up messages if they did not download the app. The Task 5.1 memo contains details about the research team's specific actions and responsibilities concerning the invitation process.

5) Step Five: Monitoring and Evaluation

The fifth step involved constant monitoring of the daily increase in registered users. This data enabled the evaluation of the effectiveness of the recruitment process. Based on this assessment, reminder emails were sent to non-registered sign-ups if necessary.

6) Step Six (if needed): Encouraging Registration

If needed, the final step entailed checking whether a sign-up completed the app registration. If not, the process included two rounds of reminder emails, dispatched one and three days after the initial invitation. These reminder emails were designed to encourage potential users to register for the app and actively participate in the Pilot program.

On average, it took 2.5 days between user registration and their first trip. For those who actively used the system, it took about 9.1 days to establish a habitual trip.

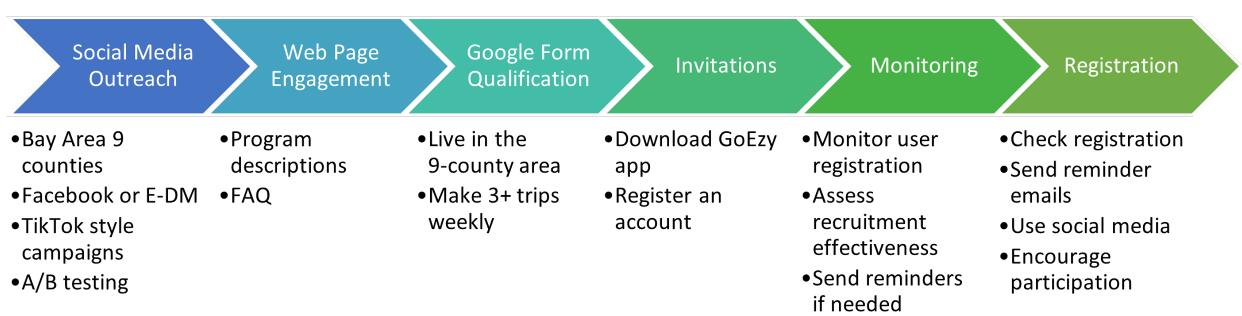


Figure 3-2: User Recruitment Flow

More details and lessons learned from the participant recruitment effort can be found in the Task 3.2.2 and Task 5.1 memos.

3.4 Behavior Design and Implementation Framework

3.4.1 D-BIAS Behavior Approach for Pilot Evaluation

The D-BIAS four-step behavior approach is an innovative and empirically proven implementation framework used for designing and executing the Pilot. It is comprised of the following four phases:

1. **Diagnose Behavior**: This phase involved defining measurable outcomes and behaviors of interest. It aimed to understand the specific context and its impact on behavior, while also identifying the drivers of the desired behavior and the barriers to change. Qualitative research, interviews, data analysis, and a literature review for the Pilot were conducted during this phase. The renowned behavioral science model, BJ Fogg's B=MAP (behavior change = motivation + ability + prompt) model, was used to assess the barriers to change (Fogg, 2009).
2. **Intervene**: Building on the insights from the diagnostic phase and leveraging established behavioral science methods, this phase was dedicated to designing interventions or solutions that effectively address the identified barriers. It incorporated the insights gained during the first phase to craft appropriate interventions.
3. **Assess**: The Assess phase involved conducting randomized evaluations to understand which interventions worked, why they worked, and how they affected different customer segments. To evaluate the chosen interventions, one or more randomized controlled trials were implemented. During this phase, data collection procedures were finalized, and the trial was continuously monitored to ensure adherence to specifications, followed by thorough analysis. From the analysis, changes in incentive structures and messaging were made to the initial Pilot design to personalize the approach to the participant.
4. **Scale**: In the Scale phase, the focus was on presenting generalizable insights, useful rules of thumb, and recommendations on how to extend the most successful solutions to a larger scale. By combining the results of the randomized controlled trials, this phase provided valuable recommendations for scaling up the most effective interventions.

The definitions of terms used in this section were:

- **Experiment**: The overall framework and efforts that were associated with targeting predictable/habitual or non-habitual trips.
- **Incentive**: Monetary or non-monetary engagement with the participants.
- **Trial**: Activity of sending out the incentives as well as observing and recording the participant responses.

3.4.2 Definition of Habitual versus Non-Habitual Trip-Making Behavior

This study differentiates both habitual and non-habitual trips in the experiments. Habitual and non-habitual trips are defined below.

Habitual Trips

Habitual trips are the regular, routine journeys that individuals frequently undertake. They follow predictable patterns, fixed schedules, and often involve repetitive destinations. Examples include daily commutes to work or school, regular visits to places like grocery stores or fitness centers, and recurring activities like picking up children from school. Habitual trips are an integral part of one's daily or weekly routine, and they typically use familiar modes of transportation along familiar routes. Factors like job location, residential area, and daily responsibilities influence these trips.

Non-Habitual Trips

Conversely, non-habitual trips are infrequent or occasional journeys that deviate from an individual's usual travel patterns. These trips are less predictable and might involve exploring new destinations, visiting friends or family outside the usual travel radius, attending concerts or conferences, or engaging in leisure activities that are not part of the daily or weekly routine. The choice of transportation for non-habitual trips may vary based on factors like distance, purpose, and availability.

Decision-Making and Behavioral Dynamics

Habitual and non-habitual trips involve distinct decision-making processes that influence travelers' choices. With habitual trips, individuals tend to stick with familiar travel modes due to the repetitive nature of these journeys. However, providing advanced information about active and shared transportation options can encourage users to consider mode changes for future similar trips. On the other hand, non-habitual trips involve unfamiliar and uncertain situations, making users more open to exploring various transportation options. Still, individuals might hesitate to take risks by opting for unfamiliar modes during these one-time trips to unfamiliar destinations. The interplay between familiarity and novelty highlights the importance of distinguishing between these two trip types in conducting behavior change programs. Such differentiation allows for valuable insights into understanding and addressing the specific dynamics of habitual and non-habitual travel behaviors.

Habitual Trips Formation

A habitual trip is defined as a recurring pattern of travel choice behavior, characterized by a consistent Origin-Destination (OD) pair and departure time interval (T), undertaken on different days. The "habitual OD" refers to the aggregation of many such habitual trips. Any travel that deviates from this pattern is classified as a non-habitual trip. While behavior changes related to non-habitual travel choices might impact short-term congestion, lasting solutions require focusing on altering habitual trip mobility options, i.e., changing habits.

3.4.3 Mobility Options Discovery (MOD) and Second-Best Option Identification

A traveler is more likely to try a suggested new mode if it is contextually relevant, attractive, and personalized. Metropia’s Mobility Options Discovery (MOD) module searches for available sustainable modes for each habitual trip, calculates the relative attractiveness of each mode using the concept of utility, and suggests the second-best mode option to driving.

For example, as illustrated in Figure 3-3, when a user drives from an origin (O) to a destination (D), there may be multiple travel mode options available, such as public transit, walking, cycling, or a combination of sustainable mobility options. Based on the characteristics of each mode option (e.g., access time, in-vehicle travel time, number of transfers, etc.), the mode utility (a linear combination of these mode attributes), and the relative attractiveness (in terms of choice probability) of each mode are calculated.[4]

In this study, a transportation mode that had more than a 10% probability was considered appealing/ attractive to the users.[5] For a given O-D pair, multiple modes could have an attractiveness greater than a 10% probability. In most O-D pairs, driving was the most appealing mode with the highest probability. The best mode option next to driving was referred to as the second-best option throughout this study.

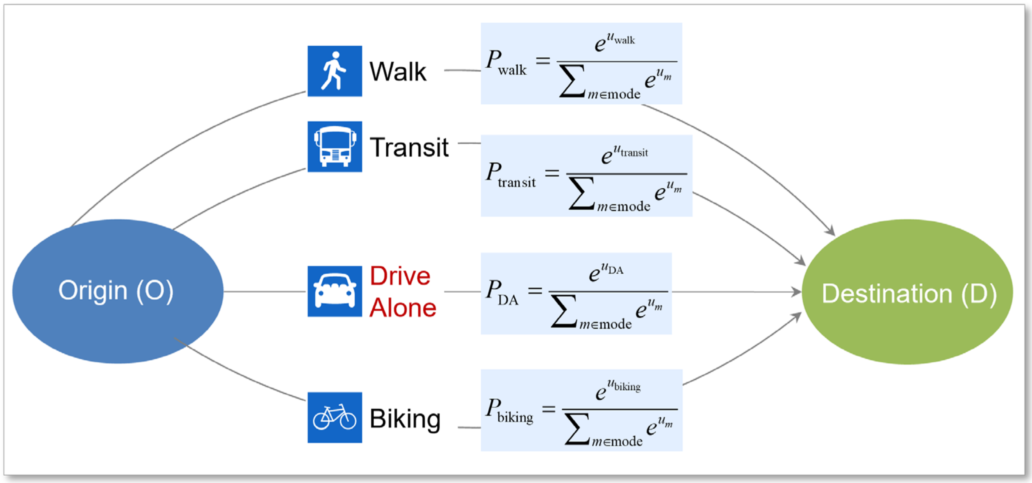


Figure 3-3: Visualization of Mode Options

3.4.4 Suggestion Tiles

All the messages and incentive related communications throughout the experiments were delivered via both push notification and in-app "suggestion tiles." Suggestion Tile sample screenshots are illustrated in Figure 3-4 to Figure 3-6 and a description is provided below.

- **Information (Info) tile**: Provides coaching information that can help frame the user's mindset about behavior change. Information can include a description of the benefits of the change—for example, an information tile will highlight the advantages of changing the departure time or to a transportation mode that would reduce congestion.
- **Action tile**: Calls upon the user to perform a specific action and how to do it. For example, it can convey the expected time savings if they leave 30 minutes earlier or provide one or two bus departure times and routes that may be a reasonable substitute for a drive-alone trip and that allow the participant to use their commute time more efficiently.

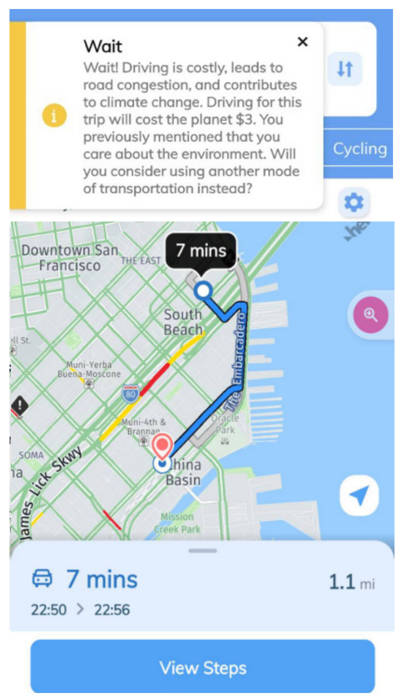


Figure 3-4: Experiment 1 Messages

[4] See Equation (1) in Section 7.5.1

[5] Mode options with attractiveness less than 10% are sometimes referred to as "infeasible" in this study, since it is highly unlikely that a participant would consider the mode to be a reasonable alternative.

- **Action tile with a variable monetary incentive**: Works like an action tile with the bonus that if the user takes the suggested action, they will receive a specific reward. The reward is visible to the user on the tile and is controlled by the backend system rules.

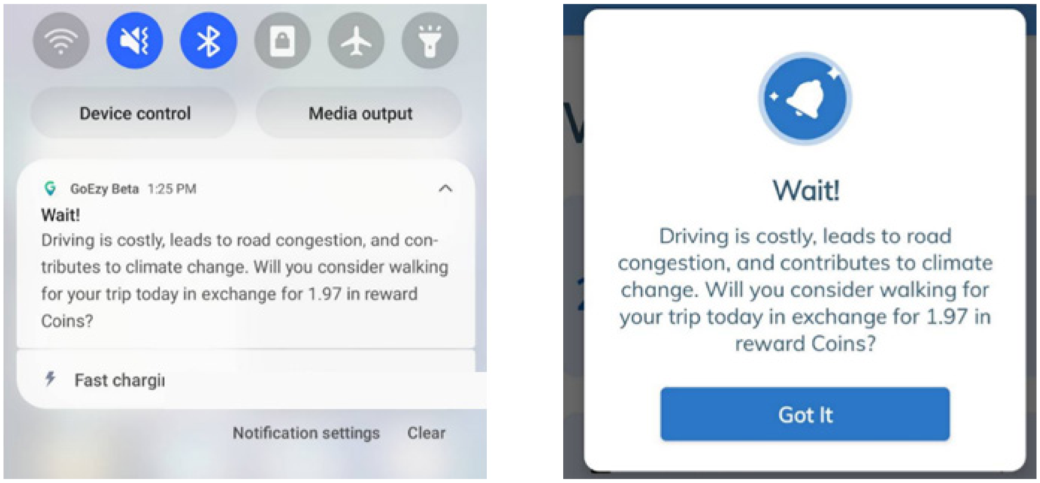


Figure 3-5: Info Tile Example of Experiment 2 Messages

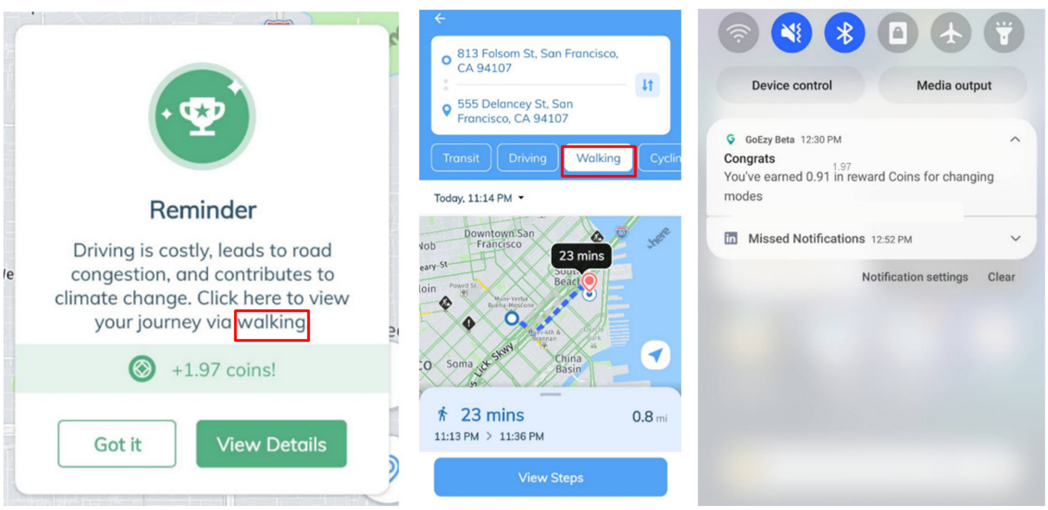


Figure 3-6: Action Tile Example of Experiment 2 Messages

3.5 Experiment Design

In the Pilot, the experiments were administered via Metropia's GoEzy app. As shown in the user journey map in Figure 3-7, users who enrolled in the experiment were prompted to download the Metropia GoEzy app. Upon installation, users were presented with various tiles based on set conditions and prompted to respond. As users traveled using Metropia's GoEzy app, their trips were identified as either habitual or non-habitual and allocated into corresponding experiments. In Experiment 2, users received incentives if they took the suggested mode change action for their trips.

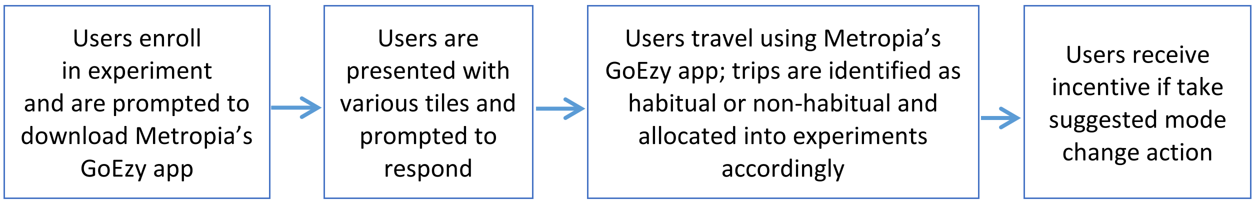


Figure 3-7: User Journey Map

Both Experiments 1 and 2 were designed as Randomized Controlled Trials (RCTs), which are considered the 'gold standard' of experimental design. RCTs allow researchers to assess the causal relationship between the explanatory variable(s) and the outcomes of interest. Participants were randomly assigned to either the treatment group(s) or the control group which received no messages or incentives. Outcomes were then compared across all groups to determine if there was a statistically significant difference between the control and treatment groups, as well as among the treatment groups.

When designing an experiment, it is crucial to ensure that it can effectively detect a "true effect" and the associated probability. The Minimum Detectable Effect (MDE) refers to the smallest effect size that is meaningful. For example, detecting an effect of 2% or less would not be cost-effective for a given intervention. Additionally, the concept of "statistical power" or "sensitivity" is relevant. Power represents the likelihood of detecting a true effect from an explanatory variable if such an effect genuinely exists. A higher statistical power increases the likelihood of detecting an effect. Typically, a power of 80% or greater is considered sufficient, indicating that if the same experiment were conducted 100 times, an effect would be identified in approximately 80 instances.

For the Pilot program, MDE was set at 3% and the "power" value was established at 80%, which aligns with typical values for studies of this kind based on existing literature (lucilemouse, 2016; Bloom, 1995). Setting the MDE value at 3% does not imply that detecting an effect at 2% or lower is impossible. However, an effect size smaller than the MDE might not be considered meaningful or substantial enough for the purposes of this study. Additionally, "power" is utilized in determining the required sample size, considering the number of interventions to be trialed.

3.5.1 Experiment 1 Design

Experiment 1 was designed to assess the efficacy of a behavior change program targeted at non-habitual, driving-based trips. It was inspired by existing research on the effectiveness of informational nudges that incorporate active choice-based messaging and loss aversion. Active choice language highlights to individuals that whatever action they are taking (or not taking) is a voluntary choice on their part, while loss aversion refers to the fact that people experience losses as more severe than gains of equivalent value.

The primary research questions for Experiment 1 are as follows:

- Does suggesting (i.e., nudging) an active or shared mode of transportation make participants more likely to shift away from driving?
- Does information about the relative social (e.g., congestion) and environmental (e.g., climate change) costs of different modes of transportation shift user behavior?
- Can users' self-image concerns[6] be leveraged (i.e., reminding individuals of their previously stated environmental concerns) to generate behavior change?

Given the limited information available on planning non-habitual driving trips in Experiment 1 and the necessity to strategically allocate the finite incentive budget, participants were not offered any monetary incentives. Instead, the intervention comprised only informational nudges. As illustrated in Figure 3-8, trips were equally distributed between the treatment and control groups, each having a 50% probability. Within the treatment category, non-habitual driving trips were further randomly divided into 4 treatment groups: 1) Low Social Cost, 2) High Social Cost, 3) Low Social Cost with Green principal, and 4) High Social Cost with Green principal.

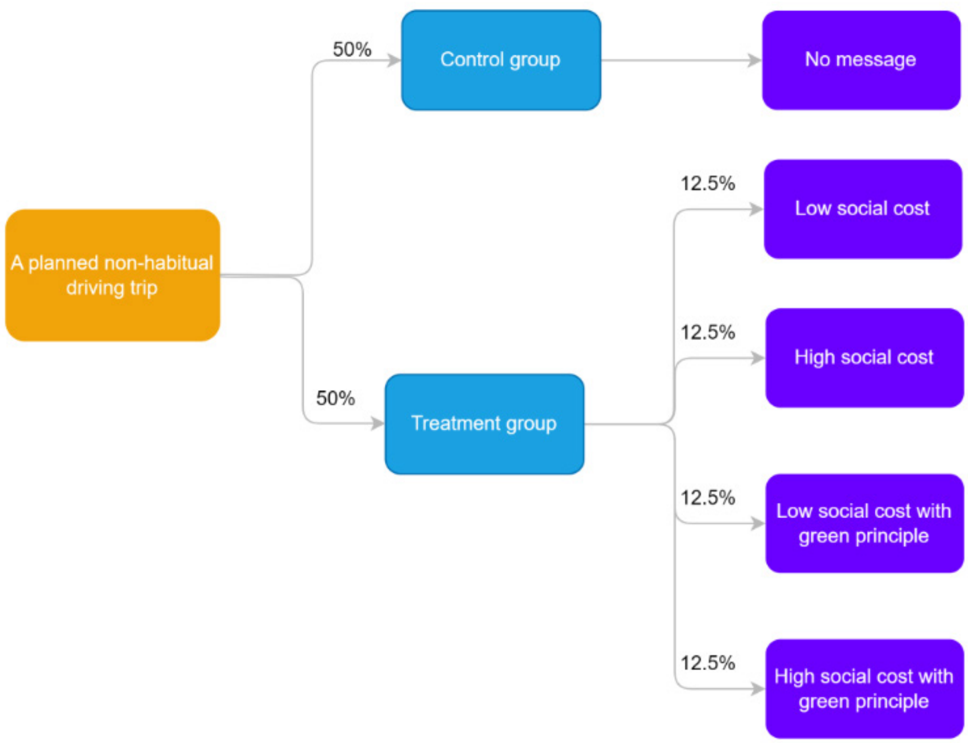


Figure 3-8: Experiment 1 Randomization Summary

[6] Self-image concerns may arise when an individuals' stated sense of self comes into conflict with their actions. In the context of this experiment, participants were reminded of their previously stated pro-environmental beliefs and nudged to change their travel behavior to align with these attitudes.

The five different randomization options are described further in Table 3-1. The messages sent to the treatment group focused on the trip cost and users' pre-stated intentions to change their behavior in favor of the environment (also referred to as the "green identity message"). The driving costs were bounded between $1 (lower bound, L) and $3 (upper bound, H), considering factors such as trip distance, estimated carbon emissions, relevant congestion, and tolls.

Table 3-1: Experiment 1 Messages

Category	Group	Message	Description
Control	Control	None	None
Treatment	Low Social Cost	Societal cost of driving - Lower bound cost estimate	Wait! Driving is costly, leads to road congestion, and contributes to climate change. Driving for this trip will cost the planet $1. Will you consider using another mode of transportation instead?
Treatment	High Social Cost	Societal cost of driving - Upper bound cost estimate	Wait! Driving is costly, leads to road congestion, and contributes to climate change. Driving for this trip will cost the planet $3 Will you consider using another mode of transportation instead?
Treatment	Low Social Cost with Green principle	Societal cost of driving - Lower bound cost estimate + green identity	Wait! Driving is costly, leads to road congestion, and contributes to climate change. Driving for this trip will cost the planet $1. You previously mentioned that you care about the environment. Will you consider using another mode of transportation instead?
Treatment	High Social Cost with Green principle	Societal cost of driving - Upper bound cost estimate + green identity	Wait! Driving is costly, leads to road congestion, and contributes to climate change. Driving for this trip will cost the planet $3. You previously mentioned that you care about the environment. Will you consider using another mode of transportation instead?

Figure 3-9 illustrates the process of users receiving information tiles on their mobile devices, along with a visual representation of the message content.

Figure 3-9: Suggested Information Tiles Journey for Experiment 1

3.5.2 Experiment 2 Design

Experiment 2 focused on habitual, driving-based journeys (i.e., trips with the same OD and departure time that have been recorded at least 3 times previously). For this experiment, targeted monetary incentives were deployed in addition to informational nudges to influence participants' behavior, as these are the journeys for which it would be most beneficial to change in the long term.

The primary research questions for Experiment 2 were as follows:

- Does suggesting (i.e., nudging) an active or shared mode of transportation make participants more likely to shift away from driving?
- What type of treatment (combination of message and monetary incentives) should be suggested to trigger participants' travel behavior change? How does this depend on participants' socio-demographics and travel characteristics?

Predicted upcoming habitual driving trips were divided into the control group and five (5) treatment groups, as illustrated in Figure 3-10. 50% of the habitual driving trips were assigned to the control group, the rest were equally allocated to each treatment group (Public Transit, Walking, Cycling, Do Not Drive, and Second-Best Mode).

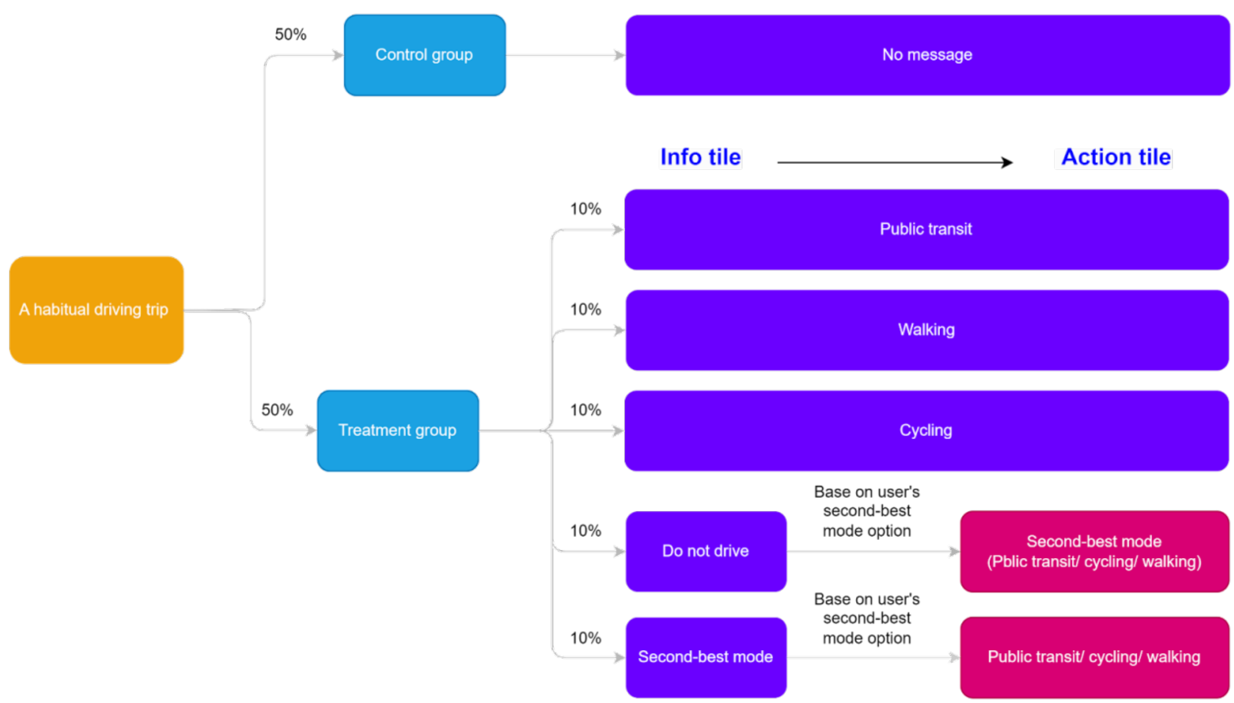


Figure 3-10: Experiment 2 Control and Treatment Groups

The control group did not receive a message or incentive, while users whose habitual driving trips were assigned to the Public Transit, Walking, or Cycling treatment groups received suggestions to switch to the pertinent mode respectively. Users whose habitual driving trips were assigned to the Second-Best Mode treatment group received a mode recommendation based on the MOD module calculation. Lastly, users whose predicted upcoming habitual driving trips were assigned to the Do Not Drive treatment group received an Information tile discouraging driving, without suggesting a specific alternate mode. If users in this group did not voluntarily change their mode, an Action tile was sent suggesting the most suitable and feasible second-best mode of transportation for their specific trip, based on the MOD module calculation, along with an incentive. In the design of Experiment 2, the allocation of incentive amounts was randomized. Table 3-2 summarizes the six different randomization options. The amount offered in the treatments follows an Erlang distribution illustrated in Figure 3-11, along with the pertinent parameters. The use of a random distribution to determine the incentive amount is driven by two key factors:

1. **Individual Variation in Willingness**. The first consideration is that each participating driver's willingness to accept an incentive to switch to the recommended mode option varies and is not known in advance. Therefore, to account for the switch behavior under various conditions, the incentive offers must be randomized. This ensures that we capture responses from various conditions in relation to the offered incentive.
2. **Erlang Distribution's Characteristics**. The second consideration is related to the use of the Erlang distribution, which has a "long tail." This characteristic allows for the generation of higher incentives (to test the response to switching) while keeping the probability of actually incurring the incentive cost relatively low. In other words, it strikes a balance between offering a potentially more enticing incentive to encourage switching while controlling the overall cost of incentives.

It should be noted that rewards were provided to the users in the form of Coins through the platform, that could be cashed for gift cards from GoEzy's marketplace.

Table 3-2: Experiment 2 Interventions

Category	Group	Intervention	Suggestion Tile(s)[7]
Control	Control	None	None
Treatment	Random Mode	Public transit nudge with incentive	Info Tile and Action Tile: Driving is costly, leads to road congestion, and contributes to climate change. We're offering you $(L~H) if you take public transit for this trip. Will you consider using public transit for your trip today?
Treatment	Random Mode	Walking nudge with incentive	Info Tile and Action Tile: Driving is costly, leads to road congestion, and contributes to climate change. We're offering you $(L~H) if you walk for this trip. Will you consider walking for your trip today?
Treatment	Random Mode	Cycling nudge with incentive	Info Tile and Action Tile: Driving is costly, leads to road congestion, and contributes to climate change. We're offering you $(L~H) if you cycle for this trip. Will you consider cycling for your trip today?

[7] Info Tiles are sent as push notifications 60 minutes prior to a predicted trip. Action Tiles may be sent 15 minutes before a predicted departure time. Further details on the GoEzy app functionality are provided in Section 3.6.

Table 3-2: Experiment 2 Interventions

Category	Group	Intervention	Suggestion Tile(s)[7]
Treatment	Base on user's Second-best Option in action tile	Do not drive nudge with incentive	Info Tile: Driving is costly, leads to road congestion, and contributes to climate change. Will you consider using another form of transportation for your trip today? We're offering you $(L~H) if you do not drive for this trip. Action Tile: Driving is costly, leads to road congestion, and contributes to climate change. We're offering you $(L~H) if you use [SECOND BEST OPTION] for this trip. Will you consider using [SECOND BEST OPTION] for your trip today?
Treatment	Base on user's Second-best Option in action tile	Second best option nudge with incentive	Info Tile and Action Tile: Driving is costly, leads to road congestion, and contributes to climate change. We're offering you $(L~H) if you use [SECOND BEST OPTION] for this trip. Will you consider using [SECOND BEST OPTION] for your trip today?

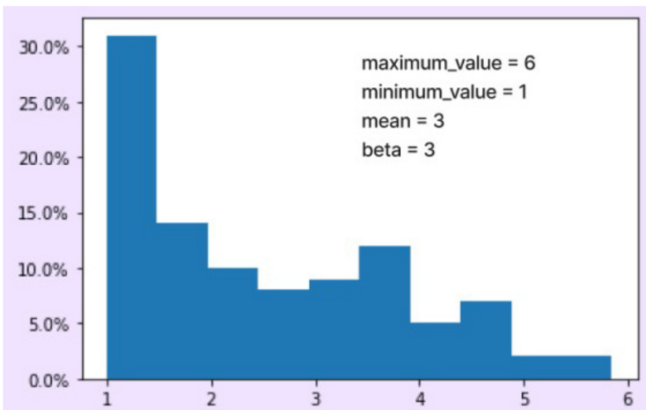


Figure 3-11: Reward Distribution

Figure 3-12 illustrates the process of users receiving information tiles and action tiles on their mobile devices, along with a visual representation of the message content.

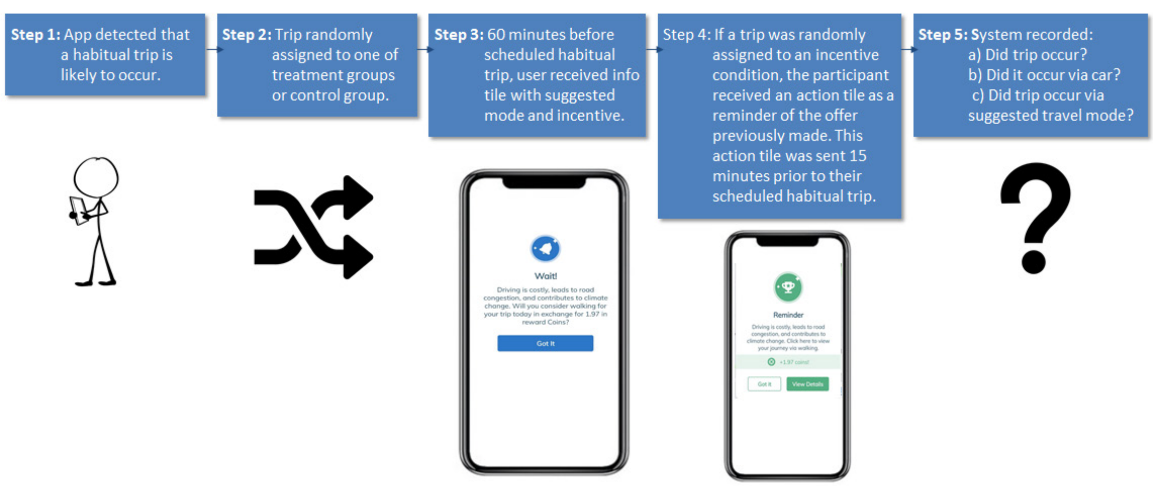


Figure 3-12: Suggested Information and Action Tiles Journey for Experiment 2

3.5.3 Analysis and Evaluation

Experiment 1 centered on planned non-habitual driving trips, which typically involve one-time decision-making processes for participants. The effectiveness of informational nudges (messages) leveraging behavioral principles, particularly loss aversion, to encourage the adoption of active and shared travel modes was assessed using Ordinary Least Squares and Linear Probability Model[8] regression models. The nudges emphasized the potential losses associated with continued reliance on driving and highlighted the benefits of sustainable modes. By providing information about the advantages of active and shared modes, such as reduced environmental impact, improved health outcomes, and cost savings, the nudges aimed to motivate travelers to consider mode shifts towards more sustainable transportation options. The impact of trip cost-related messages and green identity messages (reminding individuals of their pre-stated intentions to change behavior for the environment) was analyzed as treatments on travel mode choice.

Experiment 2 focused on predicted upcoming habitual driving trips. Ordinary Least Squares and Linear Probability models were utilized to examine the effects of a composite treatment on mode choice, which included a push notification prompting participants to open the app and access a more detailed message, along with a monetary reward offer. Additionally, the Multilevel Logistic Regression model[9] was employed to assess the effectiveness of the treatments and understand the effects of both user-level and trip-level variables on completed habitual driving travel behavior.

[8] For details on the models, please refer to Appendix 7.5.3.

[9] For details on the model, please refer to Appendix 7.5.4.

3.6 Experiment Platform Overview

3.6.1 GoEzy Mobility-as-a-Service (MaaS) Platform Overview

Metropia's Mobility-as-a-Service (MaaS) platform and its GoEzy mobile app, available for downloading from the Apple and Google stores, were the main medium for the experiment implementation. Metropia's MaaS platform transcends the traditional MaaS concept by integrating a robust behavior engine, an expanding Mobility Wallet concept, and Machine Learning (ML) capabilities.

GoEzy was designed with a user-friendly architecture that supports various modes of transportation, including Drive Alone, Public Transit, Cycling, and Walking. The app provides features such as transit, walking, and cycling navigation to help users travel from their origin to their destination. The accuracy of the dynamic traveler information within the trip planner is achieved through the integration of advanced traffic prediction, vehicle navigation, and routing capabilities. It also utilizes multiple data sources, such as the General Transit Feed Specification (GTFS) for transit and the General Bicycle Feed Specification (GBFS) for cycle sharing.

This study used the following features of the app:

- Plan door-to-door multimodal trip planning (driving, public transit, cycling, walking, intermodal).
- Turn-by-turn navigation for all modes driving, public transit, cycling, walking, intermodal.
- Optional Calendar integration for upcoming travel and integration with the dynamic incentives for departure time and mode change when needed.
- Intermodal trip planning such as trips from home to park & ride, to transit, to cycling.
- Mobility Options Discovery (MOD) to identify a user's personalized and contextually relevant mode choice set, based on the mode's characteristics (e.g., travel time, transfer time, etc.)
- Dynamic navigation to parking facilities for a user to select based on price and space availability.
- Behavior change suggestion tiles.
- A personal mobility website which complements and manages select features of GoEzy and supports behavior change.
- Point-of-interest (POI) search along with a short description (e.g., the number of parking spaces).
- Ability to use the POI as an intermediate stop (e.g., gas station) during navigation mode while en-route to the final destination.
- "Trip logs" is a feature that links with incentive programs, allowing the user to record their work-from-home trips.
- Mobility wallet to manage all the transactions, collected coins, and coins redemption for gift cards.
- Micro-survey tool that allows questions to be asked directly to the users to better understand behavior and travel patterns and to obtain other pertinent information (e.g., socio-demographics).

3.6.2 *User Interface (UI) and Presentation of Experiment 1*

The trip planning process is illustrated in Figure 3-13. Users could choose a driving route and begin their journey by following the provided instructions.

Users could tailor their choices based on when they want to leave, their preferred mode, and walking distance, as well as check the estimated arrival time of the suggested route based on their preferences. In Experiment 1, if the user was allocated to a treatment group and selected the driving mode when they entered their origin and destination in the navigation page, a message box appeared with the search result to remind the user of the cost of driving. Users allocated to the control group received the driving route without any message.

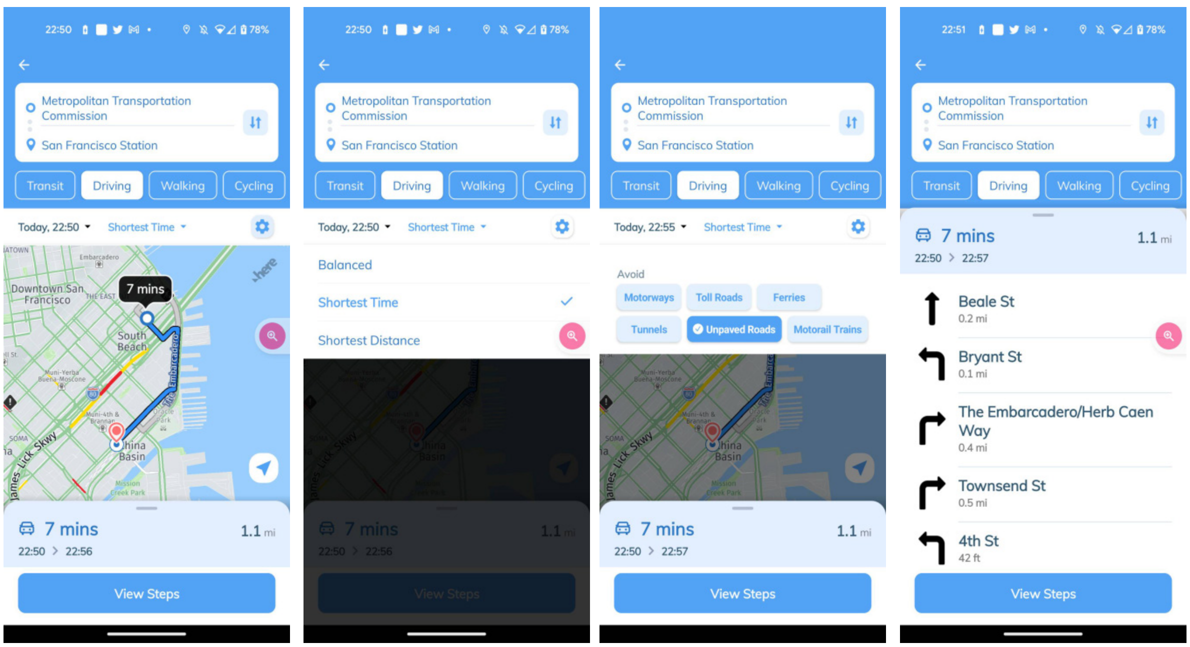


Figure 3-13: Driving Trip Planning

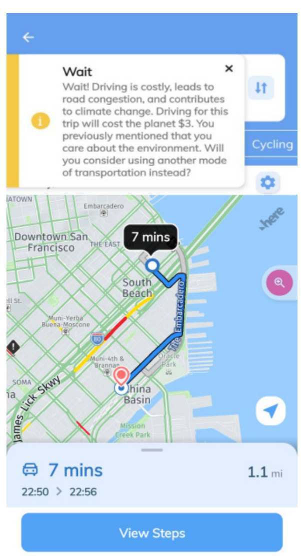


Figure 3-14: Experiment 1 Message Example

3.6.3 User Interface and Presentation of Experiment 2

Experiment 2 primarily utilized both Information (Info) Tiles and Action Tiles for delivery. Specifically, an Info Tile was sent out 60 minutes before the predicted departure time for a habitual trip. The Info Tile included a push notification that provided users with the message and the offered incentive. At the pre-set time window (e.g., 15 minutes) in which the predicted departure time for the habitual trip was located, the system sent an Action Tile to the user's app.

For the Action Tile to appear, two conditions must be met: 1) the user has their app open, and 2) the user is currently at the origin of their predicted upcoming habitual driving trip. The Action Tile contained a call-to-action and the associated incentive, such as encouraging the user to take transit or cycle.

Once the user clicked on "View Details" and completed the action as prompted by the Action Tile, he/she was congratulated for their choice and earned coins as a reward.

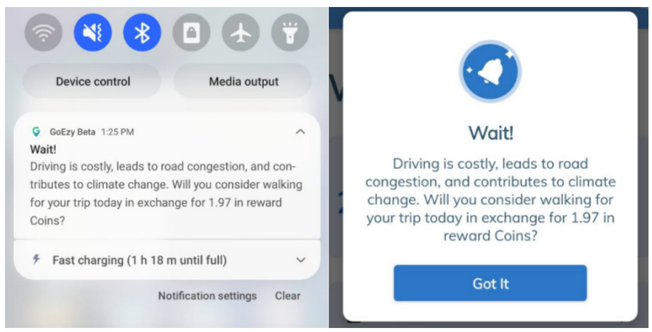


Figure 3-15: Info Tile Example

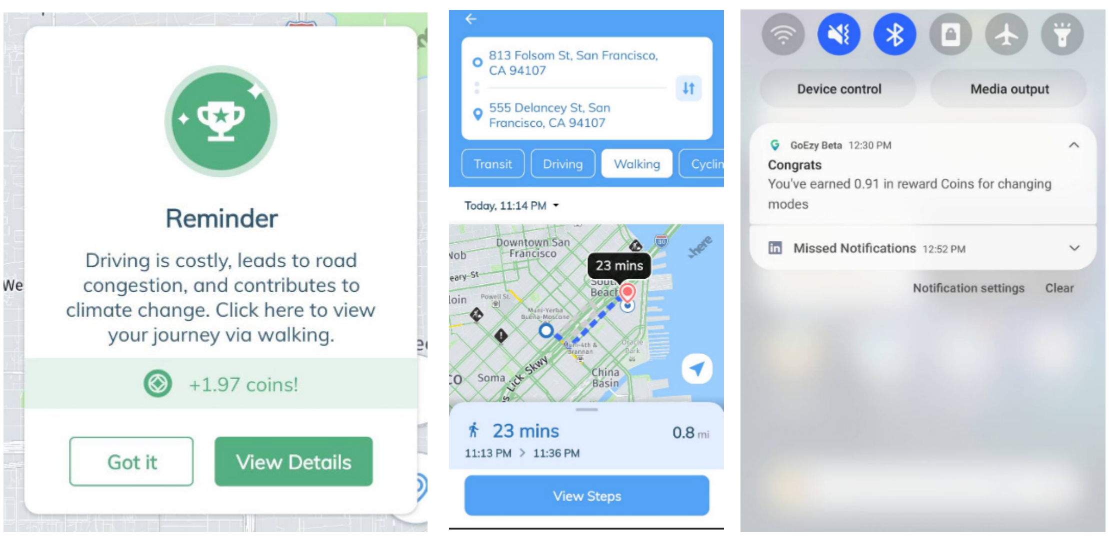


Figure 3-16: Action Tile Example

The coins could be used to redeem gift cards available in the gift card store inside the wallet. For the gift card delivery, Metropia utilized the TANGO gift card company as the primary redemption option due to the following distinct advantages:

1. Electronic redemption and delivery of the gift card and the online/offline compatible redemption process significantly reduces the administration overhead cost compared to a manual process.
2. If needed, a donation to charity could be set up as one of the cash-out options.

Figure 3-17 illustrates the implementation of coins, as well as the gift card store inside the Mobility Wallet.

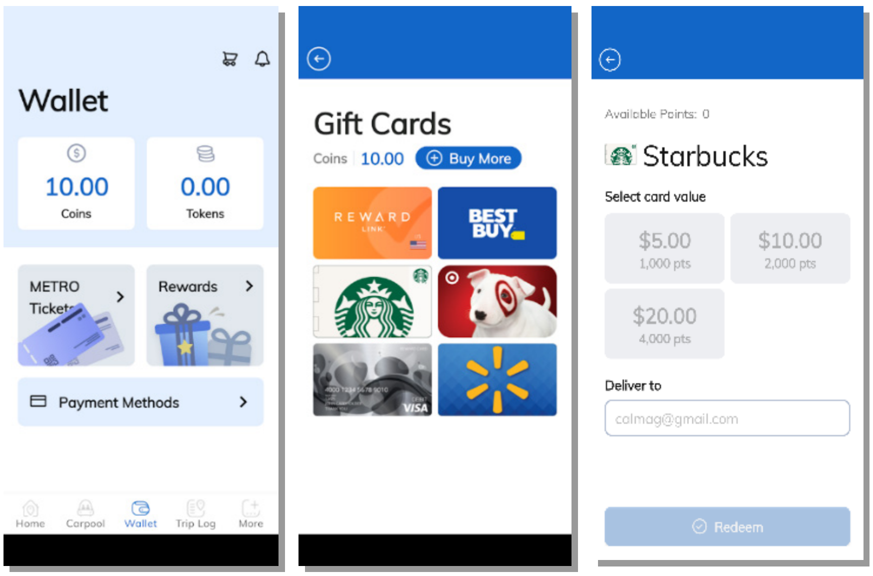


Figure 3-17: GoEzy Wallet containing Coins and Redeemable Gift Cards

4 STUDY RESULTS

This chapter offers a concise summary of the study results, which is structured into four sub-sections: Overview of Study Participants, Experiment 1: Key Results, Experiment 2: Notable Findings, and a Summary of Study Findings.

4.1 Overview of Study Participants

A total of 216 participants were recruited from May 2022 to March 2023, a total of nine months.

4.1.1 Demographics

The survey data was cross-referenced with the Bay Area population distribution from the MTC Open Data Catalog (Metropolitan Transportation Commission 2019a; 2019b). The results revealed that the survey exhibited a higher representation of male respondents (59.3%) compared to females (39.8%), in contrast to the Bay Area's nearly equal distribution of 50.6% female and 49.3% male residents.

The study included participants from a diverse age group, ranging from 24 to 75 years old, with an average age of 45.4. A significant majority of participants (43.8%) fell within the age range of 35-44 years old. This average age was higher than the median age in San Francisco, which stands at 38.3 years (U.S. Census Bureau 2022). As a result, the study naturally attracted an older age group that may have more flexibility in their lifestyle.

Besides gender and age, the participants' place of residence, household income, and education level were also analyzed. The data shows that the majority of participants resided in the counties of San Francisco (28.2%), Alameda (23.6%), and Santa Clara (18.1%). In terms of household income, participants' earnings ranged from $25,000 to over $150,000, with 26.3% falling into the high-income group and 16% in the low-income group. Moreover, a significant majority of participants held college degrees, with 46.8% having completed a four-year degree and 24.1% possessing a master's degree or PhD.

More detailed charts and diagrams are included in Appendix 7.7.

4.1.2 Vehicle Use and Ownership

In addition to the socio-demographics, analysis was undertaken pertaining to the type of vehicles participants owned since an owner of an environmentally friendly vehicle may be more prone to switch to a sustainable mode. 19.9% of the participants owned electric, fuel cell or hybrid vehicles. Finally, participants were asked about bicycle availability, with 45.8% responding positively. This nearly 50% bike availability is significantly higher than the national average.

4.1.3 Trip Type and Frequency

The survey results revealed that approximately 7.9% of participants work from home, while about 28% commute to work 1-3 days a week, indicating a hybrid work model. Notably, these findings closely align with the survey results reported by Forbes, which showed that 12.7% of individuals work from home and 28.2% follow a hybrid work model.[10]

[10] https://www.forbes.com/advisor/business/remote-work-statistics/

4.1.4 Trip Accessibility Characteristics

Among the 7,433 completed habitual driving trips and recorded trips, the average trip distance was 5.8 miles, while the average travel time was 27.7 minutes. Given that the average speed was merely 12.5 mph, these travels were mostly in a relatively congested situation.

4.1.5 Activities and Movement Patterns

Activities and movement patterns within the study area were examined using visualizations of the concentrations of all origins and destinations in the area.

Figure 4-1 illustrates the top 100 origin-destination (OD) pairs among the habitual driving trips recorded during the Pilot and indicates that a substantial majority of trips were concentrated in San Francisco, San Mateo, Alameda, and Santa Clara counties. The line thickness corresponds to a higher occurrence of OD pairs, with blue points reflecting the origin of the trip, and the red points denoting the destination. General visual inspection shows that the top OD pairs surround the bay area.

Figure 4-1: Top Habitual OD Pairs During Pilot

4.1.6 Transit Accessibility and Usage

The appeal of transit for participants' daily activities was investigated using the MOD module, as described in Section 3.4.3. In Figure 4-2, the results indicate that for ODs where the transit option has an attractiveness of less than 5%, the total transit travel time (including access, transfer, and in-vehicle times) was found to be approximately 80 minutes, with an average walk time to transit of 55.3 minutes. For these ODs, transit is much less likely to be accepted by the participants if recommended.

Also, in Figure 4-2, the remaining 40% of ODs have more reasonable walk to transit time, ranging from 2.5 to 16 minutes. Notably, for OD trips where the transit attractiveness falls between 10% and 15%, the average transit travel time is around 32 minutes. The walk/access time is evidently the major category of travel time affecting transit attractiveness. A higher mode shift to transit could be achieved by identifying areas with reasonable transit access within the current layout of the transit network.

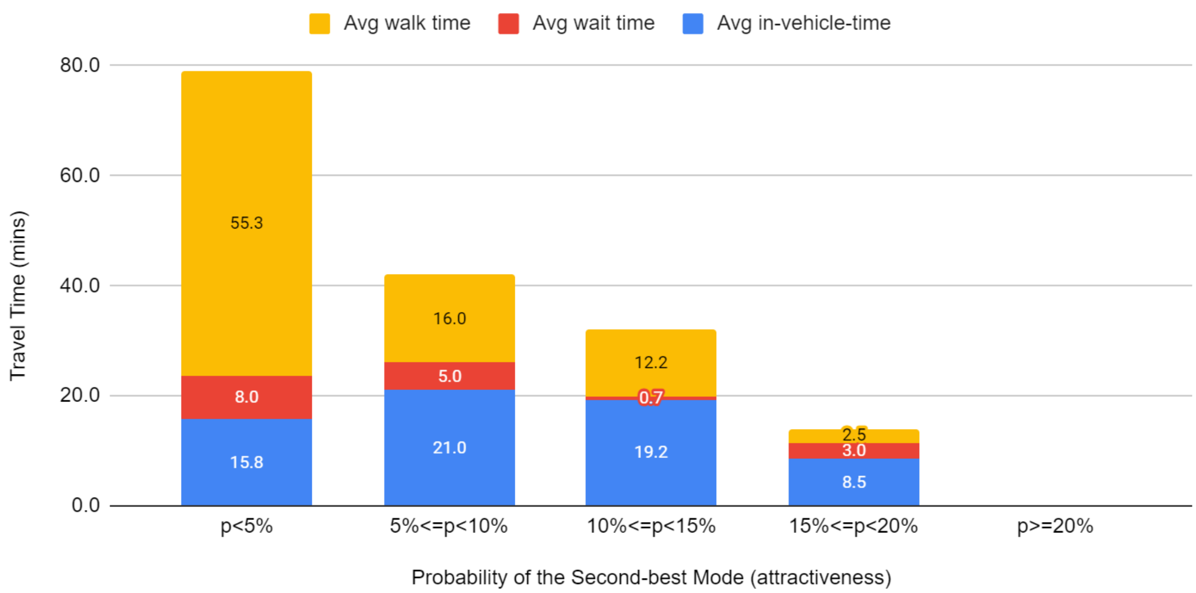


Figure 4-2: Breakdown of Travel Times by Transit Attractiveness Levels

Figure 4-3 illustrates the number of origin-destination (OD) pairs for which transit is a viable second-best option. The data reveals that nearly 60% of completed habitual driving OD pairs fall into the group with the lowest probability of transit being the second-best option (p=5%), indicating limited accessibility to transit services in these locations. Furthermore, only approximately 18% of habitual driving OD pairs have a second-best transit probability exceeding 10%. This result gives rise to two key interpretations. First, the fact that transit services are sparse explains why only 18% of habitual Origin-Destination (OD) pairs find transit to be a relatively appealing choice. Second, it highlights that a conventional, widespread transit campaign may only resonate with a small portion of its target audience. In other words, most of the campaign's resources would yield no response or action from the majority of recipients. This finding highlights the possible benefit of recommending transit only when it becomes the second-best option.

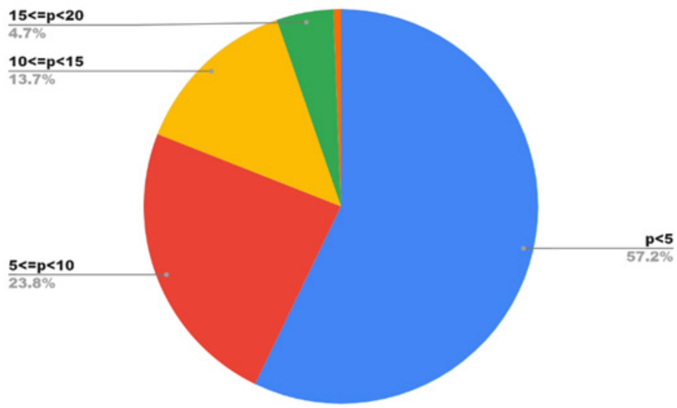


Figure 4-3: All OD Pairs Percentage in Transit Feasibility

Figure 4-4 illustrates all the OD pairs with transit attractiveness greater than 10%. The majority of these ODs are concentrated within the City of San Francisco and Oakland. Additionally, there are a few ODs located between San Mateo and Hayward, as well as the Palo Alto and Santa Clara areas. It is worth noting that although these results are derived from the limited sample collected during the Pilot, the analysis process has the potential to be expanded to cover the entire region by leveraging the regional travel demand models maintained by MTC. This broader application could provide valuable insights for targeted geo-located/fenced marketing and outreach efforts.

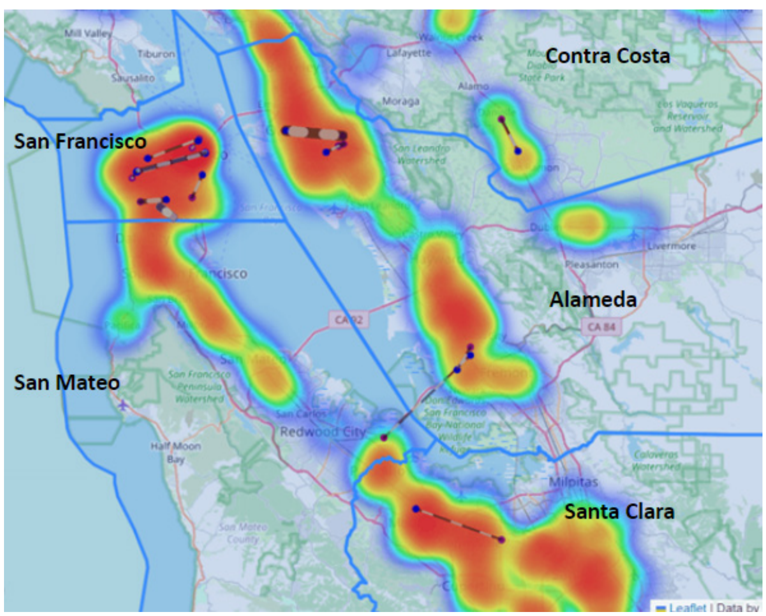


Figure 4-4: OD Pairs with Transit Attractiveness Greater than 10%

4.2 Experiment 1: Key Results

In Experiment 1, five distinct interventions (four treatment groups and one control group) were implemented, highlighting two layers of randomization. First, trips were randomly chosen to receive either a high cost or a low-cost message. The treatments at this level involved:

- Sharing an upper bound cost (fixed at $3) message of a car-based trip.
- Sharing a lower bound cost (fixed at $1) message of a car-based trip.

Second, an additional factor was introduced to the cost messages, by also sending a reminder of the travelers' previously stated green identity. The treatments at this level included:

- Sending an upper bound cost message of a car-based trip, followed by a reminder of the travelers' intention to adopt environmentally friendly behaviors.
- Conveying a lower bound cost message of a car-based trip, followed by the same green identity reminder.

The analysis included a total of 33,386 planned driving trips[11], conducted by 157 users. This experiment was not restricted to the set of habitual trips; whenever a user planned any trip using the Metropia's GoEzy mobile app, they were randomized into treatment or control groups, with the treatment group receiving one of the four available message types above.

The outcomes measured (Y variables) were:

1. Whether a trip was completed after the intervention, regardless of the mode of transport used (yes=1/no=0).
2. Whether a car-based trip was completed after the intervention (yes=1/no=0).
3. Whether a walking trip was completed after the intervention (yes=1/no=0).
4. Whether a cycling trip was completed after the intervention (yes=1/no=0).
5. Whether a public transit trip was completed after the intervention (yes=1/no=0).
6. The total number of car-based trips taken within twenty-four hours after the intervention (continuous measure).
7. The total number of non-car-based trips taken within twenty-four hours after the intervention (continuous measure).

The outputs for these analyses can be found in the Appendix 7.8.

[11] The estimation results in Appendix 7.8 may have different total sample sizes due to variations in the selection criteria of the sample (X) when estimating the effects.

4.2.1 Effect of Trip Cost Message

The analysis (Appendix 7.8, Table 7-5) indicate that the upper bound trip cost message intervention led to a substantial decrease in the likelihood of participants completing trips by car, by 86 percentage points.[12] (statistically significant at the 10% level). Note that a percentage point refers to a unit of one percent; in other words, the difference between 10% and 11% is one percentage point.

The lower bound trip cost message had a small but statistically significant effect on completing the trip by cycling following the intervention (meaning that receiving the intervention made people more likely to complete the trip by bike rather than by car).

These findings are quite intriguing. The significant 86% reduction in the likelihood of car trips suggests that providing participants with a better understanding of the hidden costs associated with driving could influence their decision-making regarding mode choice. However, interpreting the precise implications of this effect presents a challenge. It is plausible that raising awareness about the true costs of driving could impact participants' behavior positively. Nonetheless, to establish the generalizability of these effects, further studies and replications are necessary in future research endeavors.

4.2.2 Effect of Green Identity Treatment

The analysis revealed a minimal significant effect of the trip cost message (when not combined with the green identity message) on trip completion by public transit (Appendix 7.8, Table 7-6). However, overall, receiving any of the treatment conditions (i.e., trip cost estimate messages or the green identity message) did not significantly influence the likelihood of completing a trip or completing it via car, public transportation, or walking.

There was also no significant effect on the total number of trips completed using non-car modes, except for a very small (though statistically significant) increase of 0.08 percentage points in the likelihood of trips being completed via cycling and a significant positive increase in the total number of trips completed using non-car modes within the twenty-four hours following the intervention (significant at the 1% level) (Appendix 7.8, Table 7-6).

It's Important to note that "completing the trip" in this context refers to trips immediately resulting from the trip planning process. The findings indicate that displaying the message treatment during the trip planning step did not lead to any significant behavior change.

In conclusion, the study suggests that the trip cost estimate messages or the green identity message, when presented during trip planning, did not have a substantial impact on overall mode choice behaviors, except for a slight increase in completed cycling trips and non-car mode trips within the 24-hour period after the intervention.

[12] A percentage point is a unit of one percent (e.g., the difference between 10% and 12% is 2 percentage points.

4.2.3 Interaction Effects

The initial simple Linear Probability Model analysis did not yield any meaningful results. However, when examining the treatment in conjunction with other attributes (interaction effects), meaningful findings emerged. Specifically, participants defined as "flexible travelers"– those who used more than one travel mode during the first week of the experiment– exhibited significant changes in behavior after receiving the treatments.

After receiving the treatments, flexible travelers were less likely to complete their planned trip by car, with a statistically significant decrease of 2.34 percentage points[13]. Moreover, they showed a substantial decrease in traveling by car in the twenty-four hours following the intervention (a reduction of 1.83 percentage points [Appendix 7.8, Table 7-8]). Furthermore, these participants were more likely to choose non-driving modes in the twenty-four hours after the intervention, with an increase of 37.4 percentage points (Appendix 7.8, Table 7-8).

These findings suggest that individuals who already have experience with non-driving modes of transportation are more open to modifying their travel behavior and are receptive to message-based interventions that encourage non-driving travel options. These individuals can be considered the "nudgeable drivers" as they are more likely to respond positively to nudges towards active or shared transportation choices.

4.3 Experiment 2: Notable Findings

Experiment 2 focused on predicted upcoming habitual driving trips[14] and utilized the Ordinary Least Squares regression and the Linear Probability Model to examine the effects of a composite treatment on mode choice. This treatment included a push notification, encouraging participants to open the app and access a more detailed message, along with a monetary reward offer. Additionally, the Multilevel Logistic Regression model was employed to assess the effectiveness of the treatments and understand the effects of both user-level and trip-level variables on habitual travel behavior.

The control group did not receive any intervention, while the treatment group consisted of cases where sustainable mode interventions were received. Both groups encompassed two types of trips: 1) trips that did not result in actual travel, and 2) completed trips. A total of 69,384 predicted upcoming habitual driving trips were used in the Ordinary Least Squares and Linear Probability Model models, with 34,582 trips associated with the control group and 34,802 trips associated with the treatment group. On the other hand, the Multilevel Logistic Regression model specifically focused on analyzing the treatment effect on 7,433 completed habitual driving trips.

4.3.1 Effect of User Attributes

The effect of user attributes on the experimental outcomes can be summarized as follows:

Treatment and Age

Among users between the ages of 37 and 56 who received the treatment, there was a notable decrease of 1.09 percentage points in the likelihood of completing trips by driving. Additionally, there was a slight increase in the probability of using public transit and completing trips via cycling, with increases of 0.03 percentage points and 0.14 percentage points, respectively. These findings suggest that implementing the treatment for users within this age bracket can lead to significant behavioral changes, encouraging them to opt for more shifts to sustainable modes of transportation.

For users aged between 57 to 76, there was an inherent decrease of 0.05 percentage points in the likelihood of completing trips by cycling. In contrast, when this age group was specifically encouraged to use sustainable transport methods, their inclination to choose cycling increased by 0.04 percentage points (as detailed in Appendix 7.9, Table 7-11). These results demonstrate the potential for targeted interventions based on age groups; however, given the inconsistency in these findings, we would caution against over-interpreting these findings. Further research is needed to understand more fully how age may impact individuals' receptivity to transportation modal shift interventions. In the 37 to 56 age bracket, the treatment had a clear positive effect. It not only reduced driving habits but also promoted the use of public transit and cycling. In contrast, for those aged 57 to 76, even though there was a natural tendency to cycle less, the treatment still managed to boost their cycling behavior.

[14] The phrase "predicted upcoming habitual driving trips" refers to a predetermined list of intervention trips scheduled for each day of the experiment. These trips were assigned in advance and were accompanied by suggested modes of transportation, which were allocated based on probability. Essentially, if the same habitual trip occurred on different days within the experimental schedule, it had the potential to receive different interventions (either in the control group or treatment group) or suggested modes of transportation within the treatment group.

Treatment and Mode Flexibility

As in Experiment 1, a subset of participants was flagged as “flexible” travelers if they used more than one mode during the first week of the experiment. Among flexible users who received the treatment, there was a significant increase in the likelihood of completing trips via non-driving modes, as well as an increase in the likelihood of walking. Although there was also a 0.03 percentage point increase in transit use, and a 0.18 percentage point decrease in the likelihood of completing driving trips, these changes were not statistically significant (Appendix 7.9, Table 7-12).

The results indicate that the treatment had a positive impact on promoting non-driving modes and walking among flexible users. However, the changes in transit use and driving trips were not statistically significant, suggesting that the results may not be generalizable outside of this study. Overall, the findings highlight the importance of considering user flexibility and behavior patterns when designing interventions to promote sustainable travel choices. The treatment appears to be more effective in encouraging walking among flexible users.

Bicycle Ownership

Table 7-10 in Appendix 7.9 indicates that "bicycle ownership” had a strong influence on increasing the likelihood of switching from driving to bicycling. These findings are consistent with previous research, such as the study conducted by Fitch et al. (2022), which found that implementing a bicycle lending program can lead to a substantial increase in bicycle commuting. Additionally, Fitch (2019) demonstrated that electric bicycles can significantly increase cycling while reducing reliance on driving. Moser et al. (2018) also found that regular use of e-cycles can help establish a new habit of using sustainable transportation.

Residential Location

Moreover, the analysis has found that residents of Contra Costa, San Francisco, and Santa Clara counties were more likely to opt for non-driving modes of transportation. There was a marked response in San Francisco County, particularly in the zip codes of 94122 and 94118. In Contra Costa County, cities like Danville (94526) and Antioch (94509) showed notable receptiveness. Within Santa Clara County, areas such as Palo Alto (94303), Los Altos (94024 and 94022), San Jose (95123 and 95132), and Campbell (95008) also registered increased responsiveness. Several of these areas also happen to have high transit attractiveness according to the findings and discussions in Section 4.1.6, suggesting that residents in areas with higher transit (or other non-driving modes) attractiveness are likely to be more responsive to TDM campaigns. At the same time, residents of some of the transit-rich areas shown in Figure 4-4 were not especially responsive to the interventions, implying that other factors may also be contributing to the different outcomes that were observed across different parts of the Bay Area.

4.3.2 Effect of Trip Characteristics

The study involved analyzing Origin-Destination (OD) pair data to investigate how travel time and distance influence changes in transportation behavior.

Across all modes of transport, a total of 1,510 predicted upcoming habitual OD pairs were identified, with 1,206 of these OD pairs made by car. The data revealed that for OD pairs where users had taken the incentive and switched to non-driving modes, both the average travel time (22.9 minutes vs. 26.6

minutes) and trip distance (3.7 miles vs. 6.1 miles) were considerably lower compared to those who never switched modes. Additionally, the standard deviation, a measure of variability, was also lower for both travel time (21 minutes vs. 25.1 minutes) and trip distance (3.9 miles vs. 7.5 miles) among those who switched.

Based on further analysis using Multilevel Logistic Regression, it was found that:

- Promoting walking as a mode of transport for trips less than 3 miles significantly influenced individuals to alter their usual mode of travel. In practical terms, this means there's a 47% increase in the likelihood of individuals choosing non-driving behavior.
- For trips between 3 to 10 miles, suggesting cycling as an alternative to motorized transport had a considerable impact. When cycling was suggested, individuals were considerably more likely to switch to a non-driving mode, demonstrating a distinct preference for cycling in this distance range.
- For trips with an average duration of less than 5 minutes, a significant shift towards choosing sustainable transportation modes was observed.
- Weekday trips (Monday - Friday) were more likely to shift to non-driving behaviors than weekend trips (Saturday – Sunday).
- This evidence suggests that shorter OD trips, which naturally take less time, are more responsive to the treatment encouraging a switch from driving to non-driving modes.

4.3.3 Effect of Messages

The Linear Probability Model and Multilevel Logistic Regression models result suggested that:

> Receiving a message suggesting a second-best travel mode significantly increased the likelihood of the trip being completed using a non-driving mode.

- The composite treatment[15] had a small but statistically significant effect, increasing the likelihood of users completing their habitual driving trips by non-car modes (a difference of 0.2 percentage points).
- However, the aggregate results do not indicate a preference for any specific travel mode such as walking, cycling, or public transit (Appendix 7.9, Table 7-13).
- Following assessment of the composite treatment, the effect of specific message interventions on travel mode choice was assessed. (Appendix 7.9, Table 7-13).
    - Receiving the "Do Not Drive" message:
        - The likelihood of participants completing the trip via a non-driving mode increased 0.38 percentage points, indicating a 17% increase as compared to the control group.
        - The likelihood of completing the trip via biking increased 0.16 percentage points, representing a 65% increase relative to the control group.
    - Receiving the Second-Best message:

[15] The composite treatment in the experiment involved a push notification, encouraging participants to open the app and access a more detailed message, along with a monetary reward offer.

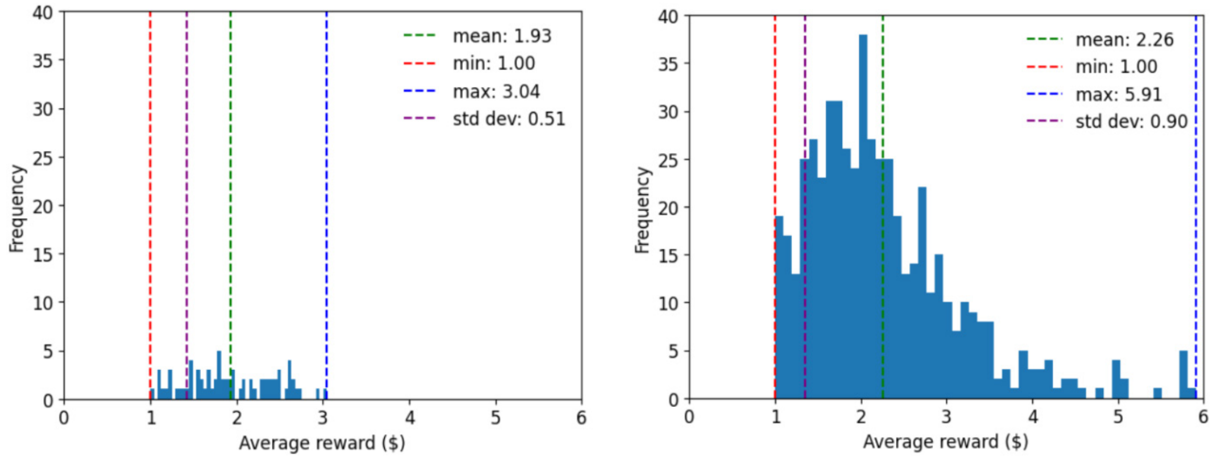
- The likelihood of completing the trip via car decreased by 0.83 percentage points, indicating a 6% decrease relative to the control.
- The likelihood of completing the trip by any non-driving mode increased by 0.46 percentage points, indicating a 21% increase relative to the control group.
- The likelihood of completing the trip by walking increased by 0.44 percentage points, translating to a 22% increase compared to the control group.

- The treatment did not have an effect when driving was the only attractive travel option. This suggests that the treatment is only effective when other attractive travel options in terms of time and distance are available. (Appendix 7.9, Table 7-15)
- When individuals received a suggestion tile promoting walking, they were more inclined to choose walking during peak hours. However, intriguingly, when presented with a suggestion tile promoting cycling, they were less likely to opt for cycling during peak hours.

4.3.4 Effect of Incentive

For the group of Origin-Destination (OD) pairs that switched to non-driving modes, the average reward ranged from $1.00 to $3.04, with a mean value of $1.93. Conversely, the group that did not switch modes was presented with higher average rewards, ranging from $1.00 to $5.91, with a mean value of $2.26. These results might seem counterintuitive, but they can be explained as follows:

- As shown in Figure 4-5, the majority of the random mode and incentive suggestions were not accepted by the participants, despite having a higher maximum and average in the distribution. This suggests that transportation mode choice decisions are often influenced by various factors and are not easily swayed by incentives alone. For example, participants may have constraints such as needing to pick up or drop off their children, which prevents them from changing their mode of transportation. Additionally, participants may be hesitant to accept random mode suggestions if they involve long walks, extended in-vehicle time, or safety concerns, even if the reward is within the defined range in this study. Mental barriers learned from the survey discussed in Chapter 2 could also play a role in their decision-making. These participants are likely to be considered non-nudgeable drivers.
- On the other hand, the few offers that were accepted provided valuable insights – users do not require substantial rewards to make a change. These participants are likely to be considered nudgeable drivers.



(a) Changed to Non-Driving Mode (b) Did not change to Non-Driving Mode

Figure 4-5: Incentive Reward Distribution by Following Suggested Mode

Further categorization of the nudgeable drivers revealed two groups: those who were presented with the second-best mode option and those with a random mode option. The average reward for the second-best mode treatment group was $1.90, while the random mode treatment group had an average reward of $2.04. The analysis indicates that when users are presented with a feasible and relatively attractive sustainable mode, the average rewards tend to be lower. Figure 4-6 illustrates the distribution of rewards for these two treatment groups.

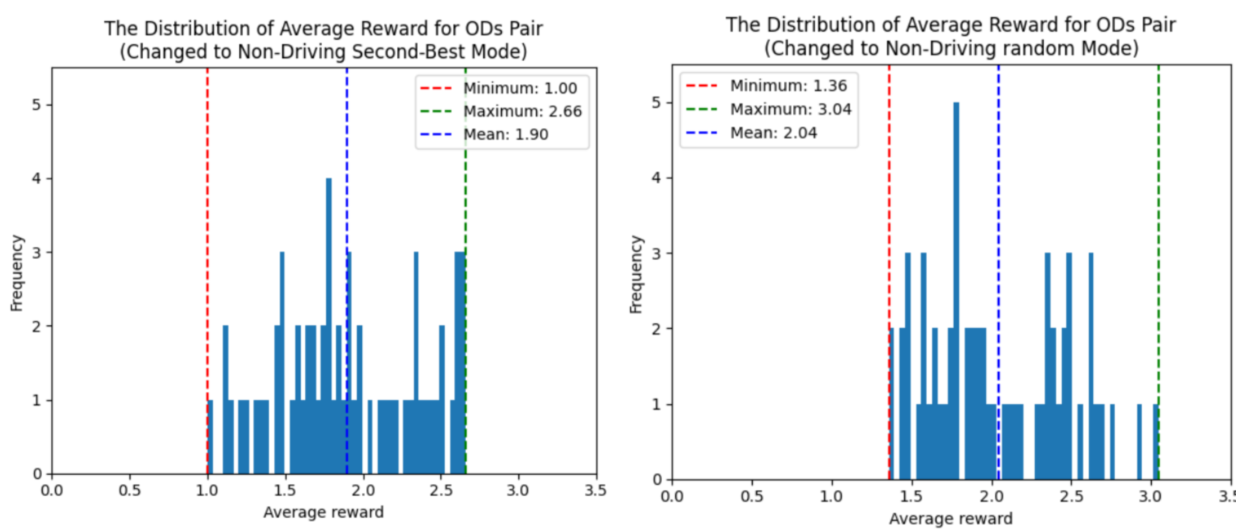


Figure 4-6: Distribution of Rewards with the Second-Best Mode Options vs Random Options

The Linear Probability Model and Multilevel Logistic Regression models further statistically revealed the following:

- Considering incentives in isolation from other interventions does not demonstrate a significant effect overall (Appendix 7.9, Table 7-16)
- With an incentive of $3, there was an increase in the likelihood of users completing their habitual trips using intermodal transportation options (i.e., incorporating transit and walking when using other modes like cars or bike) for their trips. (Appendix 7.9, Table 7-16)
- With an incentive value of $5, there was a significant increase in the likelihood of users completing their habitual trips using intermodal transportation options. (Appendix 7.9, Table 7-16)
- Randomly suggesting walking and cycling with rewards corresponded to a 5% and 4% increase in the likelihood of a user shifting to the mode, respectively.
- Presenting the second-best option increases the likelihood of choosing non-driving modes for the trip.

4.4 Summary of Study Findings

Nudgeable drivers do exist.

The study findings found that nudgeable drivers are those over the age of 37, with access to multiple mode options, and who own bicycles. Residents in specific counties, such as Contra Costa, San Francisco, and Santa Clara, also showed higher responsiveness to the interventions. There was a marked response in San Francisco County, particularly in the zip codes of 94122 and 94118. In Contra Costa County, cities like Danville (94526) and Antioch (94509) showed notable receptiveness. Within Santa Clara County, areas such as Palo Alto (94303), Los Altos (94024 and 94022), San Jose (95123 and 95132), and Campbell (95008) also registered increased responsiveness. Participants were easier to nudge to different modes for trips with shorter travel time and distance in general, and they were more likely to switch to walking for trips under 3 miles and cycling for trips under 10 miles. Nudges and interventions were more effective on weekdays compared to weekends. Messaging strategies like "Public Transit" had no significant effect on mode adoption, while the "Do Not Drive" message increased non-driving mode adoption, especially cycling. Offering incentives in the range of $3 to $5 increased active and shared mode usage, and lower rewards were needed for the second-best option to encourage behavior change.

More elaborated highlights are listed below.

1. **Characteristics of nudgeable drivers**:
    - ***Are older working-age adults***. Older participating drivers, particularly those between the ages of 37 and 56, were found to be more receptive to the behavioral interventions and nudges aimed at promoting sustainable transportation choices relative to younger drivers in the study. This age group might be more open to considering behavior changes and adopting new travel modes.
    - ***Have multiple mode options***. The participating drivers who had access to and were familiar with multiple transportation options were more likely to respond positively to the interventions. Having various mode choices might make them more willing to explore alternative travel options.
    - ***Owning a bicycle***. The participating drivers who own a bicycle were more likely to positively respond to the interventions. This suggests that these individuals may comprehend the practical advantages of using alternative transportation modes when they already have a bike. Owning a bike is a lifestyle choice, and, consequently, these individuals may also self-identify with sustainability, making them inclined to use non-driving modes when nudges are present.
    - ***Residents from certain regions have exhibited pronounced responsiveness to interventions.*** There was a marked response in San Francisco County, particularly in the zip codes of 94122 and 94118. In Contra Costa County, cities like Danville (94526) and Antioch (94509) showed notable receptiveness. Within Santa Clara County, areas such as Palo Alto (94303), Los Altos (94024 and 94022), San Jose (95123 and 95132), and Campbell (95008) also registered increased responsiveness. However, further research is needed to understand why these locations were most receptive to the experiments.

2. **Travel patterns of nudgeable trips**:
    - ***Shorter travel time and distance***. Participating drivers showed greater responsiveness to incentives for trips of shorter travel durations and distances. This suggests that promoting active and shared modes for shorter trips might be more effective in encouraging behavior change.
    - ***More likely to switch to walking for trips less than 3 miles***. Participating drivers were more willing to switch to walking as a mode of transportation for trips that were less than 3 miles in distance. Walking was perceived as a feasible and convenient option for short-distance trips.
    - ***More likely to switch to cycling for trips less than 10 miles***. Similar to walking, cycling was favored as a mode of transportation for trips that were less than 10 miles. Participating drivers might view cycling as a viable option for covering moderate distances.
    - ***Weekday trips show higher responsiveness to nudges than weekends***. Nudges and interventions were more effective in influencing travel behavior during weekdays compared to weekends. Weekday trips might involve regular commuting patterns, making Participating drivers more receptive to behavior changes.
3. **Effects of different messaging strategies**:
    - ***A blanket "Public Transit" message had no significant effect on mode adoption***. Simply providing information about public transit options without considering access, transfer times, and in-vehicle times did not result in significant changes in mode adoption. However, participating drivers were more likely to switch to transit when the option had a short walk to access the services (up to 16 minutes) and short in-vehicle times (up to 21 minutes) and an incentive was offered. Incentives helped overcome initial resistance or hesitation, providing the necessary motivation to make the switch – see the next section, "Effects of Incentives" for more information.
    - ***"Do Not Drive" message increased non-driving mode adoption, especially cycling***. Encouraging participating drivers to avoid driving for certain trips had a positive impact on promoting non-driving modes, with cycling being one of the preferred options.
    - ***Flexible travelers more receptive to non-driving options***: Those experienced with active and shared travel modes are open to message interventions and can be considered "nudgeable drivers".
4. **Effects of incentives**:
    - ***Offering a $3-$5 incentive increased intermodal transport usage***. Providing monetary rewards in the range of $3 to $5 was effective in encouraging participants to use intermodal transportation options (i.e., Transit & Walking, including other modes like cars or bike) for their trips.
    - ***Lower rewards were needed when presenting the second-best [16]option compared to random suggestions***. In the case of a habitual trip, if participating drivers are presented with a feasible alternative mode option (the second-best choice) instead of a random

[16] The second-best option is defined as the most appealing sustainable mode option next to driving for a particular origin-destination for a specific participating driver. The second-best option is highly personalized.

recommendation that may or may not work for that specific trip, a smaller incentive is required. This is intuitively clear because the second-best option is the most appealing choice after driving. When offering such appealing modes, it naturally requires fewer incentives for drivers to switch.

- ***Suggestions to walk or cycle that included rewards increased non-driving mode adoption***. Offering rewards for suggested walking and cycling trips positively influenced participants to choose non-driving modes versus providing the same suggestion without rewards. This was true regardless of whether walking or cycling was the second-best travel option.
- ***Suggestions to use transit that included rewards increased non-driving mode adoption if transit was the second-best option***. Participants were more likely to switch to transit when it was their second-best transit option with an incentive compared to when it was the second-best transit option but was suggested without a reward.
- ***Suggestions to use transit that included rewards had a positive effect on behavior change when the time taken to reach the transit station or stop (access time) was less than 15 minutes***. Offering rewards for using transit when the access time was less than 15 minutes proved effective in promoting public transportation use. This was true regardless of whether transit was the second-best travel option.

These findings provide valuable insights for developing targeted strategies to encourage nudgeable drivers to shift towards more sustainable travel modes and tailoring interventions to specific user characteristics and trip details. The ideas and concepts derived from the above findings and insights are also provided to MTC to consider in future transportation demand management (TDM) program strategy development and expansion.

5 SCALE-UP IMPLEMENTATION CONSIDERATIONS

The findings of this study hold significant promise in shaping and inspiring the practical implementation of an innovative Travel Demand Management (TDM) program for MTC. The existence of nudgeable drivers and their identifiable personas and travel patterns offer valuable insights that can enhance the cost-effectiveness of a scaled-up program. A 3-step process is proposed for scale-up implementation, as shown in Figure 5-1, with further elaboration provided in the sub-sections. The suggestions and ideas presented in this section aim to serve as a foundation for future behavior change programs. By capitalizing on the knowledge gained, MTC can develop a more impactful and efficient approach to managing travel demand in the region.

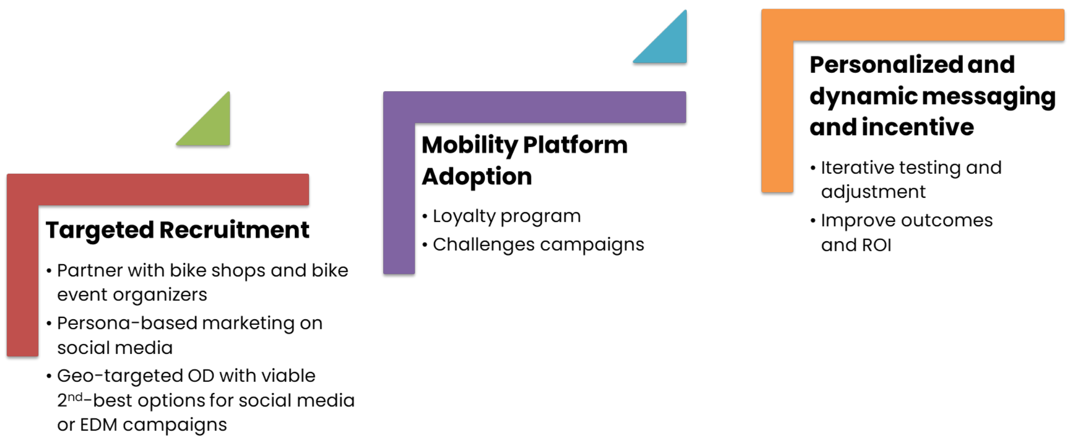


Figure 5-1: Scale-up Approach

1. Targeted Recruitment

> Nudgeable drivers exist. Reaching out to them and inviting them to participate in future campaigns is an important first step.

This study identified nudgeable drivers, and reaching out to them for future campaigns is a crucial first step in the scale-up program. To achieve this, exploring various approaches, including implementing persona-based marketing strategies on social media platforms can help target specific audience segments similar to the personas identified in this study. Tailoring messaging and content to resonate with different user groups can help to address their unique transportation needs effectively.

Additionally, MTC can use geo-targeting techniques to identify and engage potential users within specific Origin-Destination (OD) pairs that offer appealing second-best options. Using OD trip matrices from MTC's travel demand model can identify OD pairs with high trip volumes, shorter distances, and attractive second-best options as the targeted recruitment areas. This process can be executed similarly to the Mobility Option Discovery process employed in this study, ensuring effective and strategic recruitment of potential users.

Lastly, diversifying outreach or marketing approaches can help to invite more participants into future campaigns. In addition to social media, partnerships can be considered, such as collaborating with local bike shops and bike event organizers to promote TDM campaigns on the mobility platform. Joint marketing efforts could involve offering exclusive discounts or incentives to customers who participate in the campaigns or adopt the platform.

2. Mobility Platform Adoption

A mobility platform enhances engagement, and targeted outreach can be effective in improving campaign outcomes.

A mobility platform is a desirable tool to onboard, retain, coach, educate, and deliver personalized messages and incentive campaigns. Using the mobility platform and a mobile app is common in the areas of fitness and health, education and language learning, personal finance, etc. In those areas, mobile apps play a crucial role in engaging and guiding users through onboarding and coaching processes, contributing to enhanced user experiences and successful outcomes.

However, if MTC decides not to implement a mobility platform, collecting data and engaging users are feasible, but it becomes more difficult to understand user movement and activity patterns and to track responses and effectiveness. Traditional methods such as mobile web-based activity recall and logging can be employed to track and record user activities. In this approach, users are prompted to manually record their daily activities. However, this method has drawbacks, including the heavy workload it imposes on users and the potential for inaccuracies in recalling past activities.

Regarding the communication approach, an alternative method could involve using electronic surveys, SMS tracking, or QR code feedback systems at physical locations. Regular email reminders or phone notifications can also be utilized to keep users informed about specific triggers or actions.

3. Personalized and Dynamic Nudges

Delivering personalized behavioral nudging to the nudgeable drivers and continue learning and improving for the scale-up program.

In industries where mobile apps are commonly used for onboarding and coaching users, various behavior techniques are employed to enhance engagement and motivation. These techniques include personalization, gamification, goal setting, positive reinforcement, social interaction, behavioral prompts, and feedback visualization.

Targeted messaging encouraging walking for short trips under 3 miles and biking for trips between 3 and 10 miles presents a promising opportunity for behavior change in urban areas, where short trips are frequent and non-driving options are competitive.

The analysis also revealed that the attractiveness and competitiveness of the second-best mobility option significantly influenced individuals' willingness to adopt active or shared transportation. By targeting resources towards nudgeable individuals who are already inclined to consider sustainable options, interventions can be more effective and cost-efficient.

The adoption of the mobility platform would enable providing personalized trip planning and mode choice recommendations. These recommendations consider users' profile information, preferences, and available transportation options, leading to more targeted messaging and nudging towards sustainable choices.

While many app-based companies have effectively scaled personalized messaging, it's essential for MTC to assess their unique capabilities and context thoroughly. By focusing on personalization and leveraging their existing investments, MTC can make the most of their resources and intensify the impact of their behavior change campaigns.

5.1 Program Expansion Directions and Strategies

The preceding summaries highlight the valuable insights derived from the pilot program, emphasizing its potential to serve as a foundation for a non-conventional behavioral science-based Transportation Demand Management (TDM) initiative. By implementing the recommended program improvement strategies, backed by comparable funding, a substantial increase in program participants—from the current 200+ to approximately 1,000 individuals is anticipated. This expansion is envisioned due to various factors: (1) the waning impact of COVID, (2) targeted recruitment informed by the OD analysis, and (3) strategic collaborations with organizations offering broader access to bike owners.

While the heightened participant count implies an augmented incentive expenditure, projections suggest a possible reduction in per-trip incentives. The anticipated shift from nearly 300 to 2,000 trips with incentives allows for a decrease from $2 to $1.5 per trip due to the campaign being more targeted. This expanded program is forecasted to yield a reduction of 5,000-7,000 in Vehicle Miles Traveled (VMT)[17].

Implementing an expanded program, aligning with recommended best practices and engaging 5,000 to 6,000 active participants through collaborative efforts with regional transportation agency partners, is estimated to incur a total cost ranging from $750,000 to $870,000. This comprehensive initiative is projected to achieve a verified annual reduction in vehicle miles traveled (VMT) ranging from 44,000 to 55,000. This reduction is roughly equivalent to saving 10-11 tons of CO_2[18], with additional benefits such as decreased crash rates and pavement wear-and-tear. The cost breakdown encompasses various components, including technology provisioning, cloud computing, participant recruitment[19], user support, data analysis and reporting, participant retention, and incentives for behavior change. Despite the non-trivial program cost, the process ensures verified behavior change from drivers, offering a distinct advantage and higher cost-effectiveness over the traditional, self-reported generic process.

An untapped avenue for VMT reduction lies in an employer carpooling program. Survey findings, both nationally and internationally, consistently indicate a strong inclination toward carpooling as a preferred alternate commuting option among drivers. Carpooling is particularly attractive for long-distance trips. Introducing an employer carpooling program necessitates a distinct approach, involving the recruitment of interested companies initially and subsequently facilitating the matching and completion of the carpooling process. By identifying and partnering with companies prioritizing sustainability and employee commuting benefits, this initiative could unlock additional VMT savings.

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[17] The total VMT reduction was estimated by taking the estimated number of trips changed from driving trips multiplied by the average length of trips that were influenced to change from driving trips.

[18] The CO_2 savings was estimated using 22 mile/gallon fuel efficiency and 19.6 lb/gallon emission rate.

[19] In the first year, it's crucial to allocate a sufficient budget for marketing aimed at user recruitment. Establishing the program and building the brand is a non-trivial task, requiring an initial push to gain momentum. However, as the program continues over subsequent years, the expenses related to brand building and recruitment are expected to decrease. This reduction is attributed to the growing recognition and familiarity with the brand over time.

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7 APPENDICES

7.1 Relevant Literature Review

7.1.1 General Nudging Approaches

Research has shown that using incentives to "nudge" travelers to change travel behavior is a well-recognized and effective strategy. The nudge concept was popularized in the 2008 book titled "Nudge: Improving Decisions About Health, Wealth, and Happiness" written by two scholars at the University of Chicago, behavioral economist Richard Thaler and legal scholar Cass Sunstein (Thaler and Sunstein 2008). It is a concept that proposes positive reinforcement and indirect suggestions to influence the behavior and decision-making of individuals or group of individuals and that to be considered a "nudge", the intervention must be easy and inexpensive ("Nudge Theory", 2021). In addition, tailoring the incentives to the traveler or trip characteristics may lead to lasting behavior change, which is the lynchpin of a successful demand management program. Finally, a traveler is more likely to try a suggested alternative (e.g., change their mode of transportation, route, or time of departure) if it is personalized. Data that is passively observed or actively collected such as observed travel behaviors, information captured from surveys, or inferred activity type from destinations and time of day, can be used to personalize the incentives. Personalization also helps agencies to further motivate users by building targeted campaigns and to improve the overall customer experience. Given that travel behavior is influenced by a range of psychological, social, and structural factors, it is helpful to consider incentives broadly, encompassing both monetary incentives and non-monetary incentives as well as different combinations of both when designing a travel behavior change intervention.

Monetary incentives can be delivered in various ways such as upfront payments, gift cards, lotteries, or conditional rewards that vary in value. As an example, a utility company showed that when providing financial incentives to encourage water conservation, increasing the amount people received only had a marginal effect. This finding suggested that people assigned greater value to the symbolic value of receiving a gift than to the amount of the gift itself. In addition, monetary incentives can trigger different psychological mechanisms. They can appeal to a rational type of decision-making and to an irrational type of decision-making that relies on cognitive biases and heuristics. For example, since people are strongly loss averse, they dislike losses more than gains of an equivalent amount, monetary incentives can be framed as a charge imposed if people fail to meet a given target. Lotteries are another effective way to incentivize behavior that draws on people's cognitive biases because it harnesses people's tendency to overestimate the probability of unlikely events (Dolan et al. 2012). Both approaches have effectively incentivized behavior change, such as weight loss (Volpp et al., 2008).

Non-monetary incentives are also important and can target both psychological and social motivations to change travel behavior. For example, interventions that target individual psychological motives include commitment contracts, action planning, goal setting, and "foot in the door" techniques, which refers to a strategy that prompts behavior change by first asking people to comply with a small initial request (Burger, 1999)—taken together, these behavioral techniques encourage people to follow through with their intentions to change travel behavior. Several programs have included action planning and goal-setting techniques (Bamberg, 2013; Aittasalo et al., 2012).

Interventions that target social motives include social norm messaging, social comparisons, social recognition, and pro-social appeals. Social norms and social comparisons can influence behavior because individuals observe what others do to compare their behavior. Similarly, pro-social appeals can be effective if people are motivated by altruistic motives, which may be the case when shifting to more sustainable modes of travel. For example, a pro-social incentive that gave Virgin Airlines pilots the option to donate a share of the fuel costs saved to a charity of their choice was used to encourage them to adopt more fuel-efficient behaviors ("Virgin Atlantic Tested 3 Ways to Change Employee Behavior", n.d.).

Some evidence suggests that interventions that include several different behavioral techniques are more effective at shifting travel behavior (Arnott et al., 2014). This might be because they account for the various factors that affect travel behavior. As such, it is important to consider testing different combinations of both monetary and non-monetary incentives to understand what works best and assess their cost-effectiveness. It is also important to consider how different types of incentives interact, particularly when combining incentives that appeal to intrinsic or extrinsic motivations. Intrinsic motivation involves performing a task because it is personally rewarding to an individual. Extrinsic motivation involves completing a task or exhibiting behavior due to external causes such as avoiding punishment or receiving a reward. Providing monetary incentives alone to increase extrinsic motivation can sometimes undermine intrinsic motivation and decrease the passion for performing a given behavior (Frey and Jegen, 2001). Gamification in fitness apps is a successful example of promoting both intrinsic and extrinsic motivation for behavior change. People complete tasks in the form of games to earn virtual rewards while participating in greater physical activities and after-class exercises. This process makes them feel that exercising is a voluntary, exciting, and personally rewarding task rather than a forced one.

7.1.2 Monetary Incentives Studies

Over the last decade, several studies have field-tested incentives to motivate commuters to explore new mobility options (Jariyasunant et al., 2015; Ben-Elia and Ettema, 2011a; 2011b; Bamberg et al., 2003). These studies concluded that using incentives to change travel behavior, such as shifting departure time to off-peak times and increasing the use of public transportation services, is an effective strategy (Arian et al., 2018; Hu, Chiu, and Zhu, 2015; Hu et al., 2020). While the shift of travel patterns was significant during the reward period, studies have also found that the incentives were insufficient to sustain the behavior change. After the rewards were reduced or terminated, travelers tended to revert to their old behavior (Ettema et al., 2010; Kruijf et al., 2018; Thøgersen and Møller, 2008). To overcome this limitation and stretch funding made available for incentives, other studies have sought to identify target users through their feasible choice set and only reward actual behavior change (BART, 2019; Arian et al., 2018).

While research has offered evidence that rewards of monetary or material value may motivate ongoing change or drive behavior change at the outset, but it also has found that the continuation of such rewards may not offer long-lasting behavioral retention or induce permanent behavior (Martin et al., 2012) unless the intrinsic values of the new behavior are sufficiently strong to attain the new habit (Arian et al., 2019). Since most of the rewards in previous studies were presented as deterministic offers for specifically asked actions, users knew what they were being rewarded for and, in some cases, may not have gained intrinsic motivation (BART, 2019; Wendel, 2020).

Empirical evidence from consumer products design suggests that variable rewards are more effective than set rewards for causing habit formation (BART, 2019; Eyal, 2014), and that they are better at bringing attention to the intrinsic value of the new mobility option rather than the monetary value of the reward. Randomized rewards in gamification increase continued participation and engagement, which is critical to building a habit-forming product (Filippou et al., 2014). When users recognize and realize intrinsic values and indicators show that the behavior change has been sustained, incentive rewards could be tapered down, resulting in a behavior change framework that could be sustainable and cost-effective for scaled-up policies and strategies (Arian et al., 2019).

7.1.3 Non-Monetary Incentive Studies

Most of the initiatives aimed at changing travel behavior have been rigorously tested using two main behavior change techniques, providing information and enhancing self-efficacy (Arnott et al. 2014). The most communicated information types are 1) the negative consequences of car use, and 2) when, where, and how to travel using active or shared modes of travel, such as walking, cycling, and public transportation. Self-efficacy refers to one's perceived ability to achieve a given task, which is commonly applied by prompting people to set behavior change goals, plan their actions, and monitor their performance.

A study with Virgin Atlantic Airways examined how changes in the behavior of pilots can lead to a reduction in costs and carbon emissions (“Virgin Atlantic Tested 3 Ways to Change Employee Behavior”, n.d.). Based on the behavioral diagnostics performed, three techniques to encourage pilots to adopt more fuel-efficient behaviors were designed and tested: 1) informing them about their fuel efficiency performance, 2) setting efficiency targets, and 3) telling pilots that the airline would donate to charity on their behalf if they met their targets. These nudging techniques were tested in an experiment with 335 pilots for 8 months. The research findings identified setting ambitious performance targets for pilots as the most cost-efficient intervention strategy. Implementing such nudges led to a substantial savings of $7 million in fuel costs (around 500,000 kg of fuel), which translates into an abatement of about 1.5 million kg of CO_2.

Bamberg (2013) designed and tested an intervention to promote a voluntary reduction in car use by enhancing people’s self-efficacy through goal setting, action planning, and self-monitoring techniques. The approach focused on identifying and targeting the different consecutive stages people go through when transitioning to new behavior. More specifically, the intervention consisted of a phone-based marketing campaign, informing the participants of the benefit of using non-driving modes and helping them set car use reduction goals, giving them clear instructions of how to achieve them, monitoring their own progress, and finally revisiting and assessing their goals and strategies. The effectiveness of this approach was evaluated through a randomized controlled trial. The findings suggested that even though the participants were not asked to change their behavior directly, “nudging” them towards thinking about the negative consequences of their current behavior, raising awareness of new mobility options, and to the fact that changing their current behavior is both necessary and possible, resulted in significantly reduced car use and increased public transportation use, while walking and cycling remained unchanged. In comparison, the delivery of standardized informational brochures had no significant effect.

Aittasalo et al. (2012) evaluated a travel behavior change Pilot program that promoted walking to work.

The program targeted employees and was implemented with a top-down approach in different companies over six months. The intervention consisted of an initial group meeting to raise awareness on the health-related outcomes of active travel, using a pedometer to allow self-monitoring, and a series of personalized email communications aimed at encouraging participants to form behavior change intentions, set goals, and plan their actions to achieve their goals. The effectiveness of the Pilot program was evaluated using a randomized controlled trial. The results from the trial showed that the intervention led to significant but short-term effects on walking to work and walking for leisure, due to the lack of a robust incentive mechanism. While people understand the intrinsic value of walking to improve their health and using a pedometer shows progress towards their goals, the process itself may become less exciting over time. Unless rewards reinforcing the joy of walking are offered, individuals may become less motivated over time and eventually revert to their original habit. Pairing awareness and communication with an incentive mechanism supporting virtual rewards such as online walking competitions among participants, could increase the intrinsic motivation to continuing performing the task, which is something that a pedometer alone can't accomplish.

The Cycling Demonstration Towns program is an initiative to change travel behaviors by encouraging cycling as a mode of transportation. The program was launched in England with a Pilot that involved six towns. In contrast to the other two initiatives mentioned above, it addressed behavioral and structural barriers to change travel behavior, later scaled regionwide. The intervention involved a combination of town-wide media campaigns, personalized travel planning, cycle repair, cycle training services, and improvements to infrastructure for cycling. The Pilot program was evaluated using a controlled repeat cross-sectional study based on telephone surveys and cycle trips made. Net increases were found in the proportions of residents who reported cycling for at least 30 minutes once per month or 12 or more times per month (Sloman et al., 2009).

Overall, as these examples illustrate, the effectiveness of behavioral interventions to reduce car use and increase active and shared travel appears to be mixed. Some studies point towards significant shifts in travel behavior, while others provide more ambiguous results. However, evidence suggests that programs that include multi-pronged behavior change techniques that not only make people aware of the benefit of the new behavior but also feel motivated to continue doing so are more effective at shifting travel behaviors (Arnott et al., 2014).

Table 7-1 provides a summary of nudging techniques that have been applied across a range of domains.

Table 7-1: Summary of Nudging Techniques in Various Industries

Industries	Effective techniques	Results	Source
General	(1) default rules (2) simplification (3) uses of social norms (4) increases in ease and convenience (5) disclosure (6) warnings, graphic or otherwise (7) precommitment strategies (8) reminders (9) eliciting implementation intentions (10) informing people of the nature and consequences of their own past choices	NA	Nudging: A Very Short Guide (Sunstein, 2014)
Public Health	MINDSPACE: Messenger, incentives, norms, defaults, salience, priming, affect, commitments, ego	NA	Influencing behaviour: The mindspace way (Dolan et al., 2012)
Public Health	Information provision: Providing additional information about calories	While calorie information has a positive effect, some interventions may trigger compensatory behavior that results in the purchase of unhealthy items	Nudging Healthier Choices in a Hospital Cafeteria: Results From a Field Study (Mazza et al., 2018)
Public Health	Visibility enhancement: Increasing the relative distance between beverages and snacks to prevent eating snacks	The likelihood of employees taking snacking increased from 12% to 23% for men and from 13% to 17% for women when the beverage station closest to the snack station was used.	Proximity of snacks to beverages increases food consumption in the workplace: A field study (Baskin et al., 2016)
Public Health	Visibility enhancement: Placemats featuring two healthy "Kids' Meals of the Day" upon restaurant entry	Children exposed to the study placemats prior to ordering ordered a significantly greater number of healthy food components than controls ($p = 0.03$).	Effects of a randomized intervention promoting healthy children's meals on children's ordering and dietary intake in a quick-service restaurant (Anzman-Frasca et al., 2018)

Table 7-1: Summary of Nudging Techniques in Various Industries

Industries	Effective techniques	Results	Source
Public Health	Hedonic enhancements: Using salience and priming techniques to influence adult food and beverage choices	A combination of "priming" and "salience" nudges influences healthier choices.	Nudging healthier food and beverage choices through salience and priming. Evidence from a systematic review (Wilson et al., 2016)
Lifestyle	Incentives: Provide incentives through a smartphone app to increase physical activities	1.An incentives-based app can induce significant physical activity behavior change. 2.Those typically lacking motivation to exercise are most likely to be incentivized to increase their activity levels.	Physical Activity Behavior Change Driven by Engagement With an Incentive-Based App: Evaluating the Impact of Sweatcoin (Elliott et al., 2019)
Economics	Norms: Examine the effect of incentives, social norms, and implementation intentions on public transport uptake.	Social norms do not have much effect on increasing public transit usage compared with incentives in the long-term.	When Nudges Aren't Enough: Incentives and Habit Formation in Public Transport Usage (Gravert and Olsson, 2019)
Economics	Incentives: Provide subsidy for energy conservation	The natural gas subsidy appears to reduce welfare.	Efficiency and Equity Impacts of Energy Subsidies (Hahn and Metcalfe, 2021)
Retail	Customer-specific (i.e., adaptive) nudges: social norms and perceived risk	Not provided.	Designing Adaptive Nudges For Multi-Channel Choices of Digital Services: A Laboratory Experiment Design (Hummel et al., 2017)
Environment	Default: Changes to the default option	Household's consumption was automatically reduced at peak electricity demand period.	Informing Versus Nudging in Environmental Policy (Ölander and Thøgersen, 2014)
Environment	Social comparison feedback: A Home Energy Report letters were sent to residential customers comparing their electricity use to their neighbor's.	The comparative feedback was found to reduce electricity consumption by 2% on average.	Behavior and Energy Policy (Allcott and Mullainathan, 2010)
Transportation	Framing of information: Showing drivers gallons per mile rather than miles per gallon as a measure of fuel efficiency	The percentage choosing the more fuel-efficient option increased from 25% in the MPG frame to 64% in the GPM frame ($P < 0.01$).	The MPG Illusion (Larrick and Soll, 2008)

Table 7-1: Summary of Nudging Techniques in Various Industries

Industries	Effective techniques	Results	Source
Transportation	Changing the physical environment	The most important policies for promoting cycling are the provision of separate cycling facilities along heavily traveled road	Making cycling irresistible: lessons from The Netherlands, Denmark and Germany (Pucher and Buehler, 2008)
Transportation	Feedback on transport use and mobility patterns	Providing drivers with feedback on dangerous driving behavior reduced accident rates in the short term	In-vehicle data recorders for monitoring and feedback on drivers' behavior (Toledo et al., 2008)
Transportation	Encouraging walking with the help of smartphone apps: Providing always-on accelerometer-based smartphone apps	The app users increased their walking by 64%	Walking in the wild – using an always-on smartphone application to increase physical activity (Harries et al., 2013)

7.2 Expected State of The Commute

The COVID-19 pandemic created disruptions in commute habits, with fewer people driving and using public transportation, having shifted from traveling to the workplace to working from home. While telework has grown over the years, COVID-19 propelled the concept into a new reality for a large portion of the workforce. When the project commenced in May 2021, one of the initial tasks was to investigate the state of commuting. The data and literature gathered at that time primarily represented the conditions in 2021 when COVID was still pervasive. Notably, these findings continue to hold relevance because many companies have embraced various forms of hybrid work arrangements in response to the pandemic.

With vaccination rates steadily climbing and the number of COVID-19 cases trending downward in the California, many companies plan to reopen. At the end of March 2021, San Francisco moved into the orange tier, prompting several prominent employers in the City to announce the first phase of their office re-openings ("What You Need to Know About Return to Work Policies and Reopening Offices in San Francisco", 2021). This included two of the City's largest private employers—Salesforce and Uber. Uber became one of the first San Francisco companies to reopen its office on March 29 at 20 percent capacity. On May 4, San Francisco entered the yellow tier, the state's least restrictive COVID-19 tier, indicating that offices can open at 50 percent capacity. It is worth noting that vaccinated employees do not count towards the capacity limit. In May, a survey of almost 1,000 office managers primarily in the Bay Area, found that over 70 percent of those surveyed are planning to return to physical workplaces in one form or another by July at the latest ("California's Bay Area Workspaces Will Change Post-Pandemic", 2020). However, starting in early July, that tone has suddenly shifted. The Delta variant, a more contagious version of the coronavirus, is sweeping through the country. Fewer than half of Americans are fully vaccinated, exacerbating the situation, and many companies are reconsidering their return dates after objections from employees and concerns about the surging Delta variant. The CEO of Google said the company aims to have most of its workforce back in the office beginning October 18 instead of its previous target date of September 1 ("Google Delays Workers' Return to the Office until Mid-October, and Will Require Vaccinations - MarketWatch", n.d.). Their California employees who have voluntarily returned to the office are again wearing masks indoors. In early August, Twitter closed its recently reopened offices in San Francisco and New York and will indefinitely postpone other reopening plans. Facebook and Lyft announced they would delay their plan to return U.S. employees to their offices until January 2022 due to ongoing concerns with the Delta variant (Rodriguez, 2021; "Return to Office Disrupted by Covid-19 Delta Variant", n.d.). Apple also told its workforce in August that it would push back its return-to-office date from this September to January 2022 (Kelly, 2021). Goldman Sachs said on August 24 that anyone entering its offices in the United States must be fully vaccinated against COVID-19 ("Goldman Sachs to Mandate COVID Vaccine for Staff, Visitors at U.S. Offices -Memo | Reuters", n.d.).

The following provides an overview of the expected policies, traffic patterns, and commuter benefits.

7.2.1 Back-to-Work Policies Outlook

Overall, an estimated 18 percent of U.S. workers will likely work from home every day in the post-pandemic era (Calvert, 2021), more than double the 7 percent who did beforehand, said Abolfazl Mohammadian, director of the Transportation Laboratory at the University of Illinois at Chicago. In a survey released in March, employers of 174 major companies told the Partnership for New York City, a nonprofit group, that they expect more than half of office employees to work at least part-time remotely (Bloomberg.Com*,* 2021). While employers are still reviewing their policies and return-to-the-office policies may be revised, three main back-to-work models are expected: work in the office, work from home, or a hybrid model where employees are in the office a couple of days a week. The sections below provide examples of companies that fall under the two models: Full Return and Hybrid Model, while Table 7-2 summarizes expected policies by company size.

Full Return

In the Spring of 2021, most banks demanded a full return to work before September. For example, in May, Goldman Sachs asked the majority of its workers in the United States and Britain to return to the office in June ("Big Banks Are Starting to Push Back Their Return to Offices in Response to Delta Variant - CNN", n.d.). Due to the surging Delta variant, big banks such as Goldman Sachs, Credit Suisse, and Morgan Stanley are making adjustments to their return-to-the-office plan by requiring their non-vaccinated staff to continue to work remotely ("Goldman Sachs, Credit Suisse, Morgan Stanley Adjust Return-to-Office Plans amid Delta Variant Concerns | Fox Business", n.d.). A spokesperson for Goldman Sachs told FOX Business that the investment bank will require all individuals who enter its offices, including employees, clients, and other visitors, to be fully vaccinated by September 7, 2021.

Hybrid Model

In a hybrid work model, employees have more flexibility to get work done when they are most productive. In June, Forrester, a global market research firm, predicted that 70 percent of U.S. companies will pivot to a hybrid work model post-pandemic ("Forrester: Only 30% Of Companies Will Embrace a Full Return-To-Office Model" n.d.). Before the Delta variant, Facebook planned to reopen its offices in the Bay Area in May of 2021 at 10 percent capacity to start and to gradually increase to 50 percent capacity by September (Campbell, 2021). Google expected 60 percent of its global workforce to return to their pre-pandemic offices a few days a week in September, with 20 percent moving to a different office and the remaining 20 percent working from home ("Google Backtracks on Office Returns and Will Allow Employees to Work Remotely - CNN", n.d.). Uber expected its employees to return to the office at least three days a week by September 13. However, beginning in early August, some companies such as Wells Fargo pushed back their return-to-office dates to at least October (Son, 2021), while Google, Facebook, Uber, and Lyft said employees don't have to return until 2022 (Cadman et al., 2021; "Google Pushes Its Mandatory Return to Office Date into 2022 - The Verge", n.d.; "Uber Delays Return to the Office for Workers Until January", n.d.). In early June, Apple asked staff to return to the office three days a week (Mondays, Tuesdays, and Fridays) and for teams that need to work in-person to return four to five days a week, starting in early September ("Apple Asks Staff to Return to Office Three Days a Week Starting in Early September - The Verge", n.d.). However, about 1,800 employees sent the chief executive a letter calling for a more flexible approach ("Delays, More Masks and Mandatory Shots: Virus Surge Disrupts Office-Return Plans - The New York

Times", 2021). In early August, Apple also delayed its return to corporate offices at least until January 2022 due to surging COVID-19 cases and new variants (Espósito, 2021). According to Reed Hastings of Netflix in July, the company expected all its employees to return to office work at the start of September, but that will no longer be the case ("Netflix Sets Post-Labor Day Return to Office Life", n.d.). Its offices are open to staff to use (provided they are vaccinated), but employees will continue to be allowed to work from home for the foreseeable future. Asana planned a hybrid return to in-person collaboration and team gatherings for all employees ("Reuniting and Thriving in a Distributed World with Asana - The Asana Blog", n.d.). Still, it offers a Work from Home Wednesday program, setting time for individual work either at home or in the office. In early August, it told employees that offices in San Francisco and New York will reopen no earlier than February 2022 (Chen, 2021).

Policies by Company Size

The policies by the size of the company and the date of the announcement are summarized in Table 7-2 on the following page. The second column specifies the number of employees in U.S. offices, and the number in parentheses is the year when the number was collected. According to the above analysis, most large-sized companies adopt either hybrid or full in-office models, allowing their employees to adjust to the working patterns before the pandemic gradually.

Table 7-2: Policies by Company Size

Company Name	Employees in U.S.	Location	News Date	Return Date	Return Size	No. of days in office/week	Remote Size
PayPal	21,800 (2018)	Silicon Valley	11/1/2020	-	Hybrid (predicted)	2-3 days	-
HubSpot	3,387	Cambridge	1/1/2021	January 2021	70%	No more than 2 days	30%
Adobe	22,516 (2020)	Silicon Valley	1/11/2021	-	Hybrid (predicted)	2-3 days	-
Spotify	5,584 (2020)	National	2/12/2021	-	Allow employees to choose to be in office full time, at home full time, or a combination	-	-
Zillow	5,249	National	2/14/2021	-	10%	-	90%
Ford	186,000 (2020)	National	3/17/2021	July 2021	-	2-3 days	-
Microsoft	96,000 (2020)	Redmond, WA	3/22/2021	March 29, 2021	100%	-	0%
Twitter	4,900 (2019)	Silicon Valley	3/26/2021 7/29/2021	Gradual, office-by-office Close office in July	20%-	-	~80%
Facebook	58,604 (2020)	Silicon Valley	3/31/2021	May - September, 2021	10%-50%	-	50%
Netflix	12,135	Los Gatos	4/9/2021	September 6 2021	100%	4 days	0
Salesforce	36,000 (2018)	San Francisco, Palo Alto, Irvine	4/12/2021	May 2021	20%-100%	1-3 days	~80%
Uber	26,900 (2019)	Mission Bay, San Francisco	4/15/2021 7/29/2021	September 13, 2021 February 2022	100%	≥ 3 days	0%
Intuit	10,600	Mountain View	4/20/2021	August 2021	Most employees	2-3 days	
Asana	900	San Francisco	4/20/2021 7/29/2021	June 2021 February 2022	Most employees	Work from Home Wed.	-

Table 7-2: Policies by Company Size

Company Name	Employees in U.S.	Location	News Date	Return Date	Return Size	No. of days in office/week	Remote Size
JPMorgan	189,315 (2019)	National	4/27/2021	July 2021	50%~	2-3 days	~50%
Google	135,301 (2020)	Global	5/5/2021 7/28/2021	September 1, 2021 October 18, 2021	60% & voluntary	2-3 days	20%
Coinbase	1,249 (2020)	San Francisco	5/5/2021	May 5, 2021	5%	-	95%
Instacart	10,520 (2021)	San Francisco	5/11/2021	September 2021	Central operations team size of 100	≥ 3 days	70%
IBM	350,000	National	5/13/2021	April 2021	80%-90%	2-3 days	10%-20%
Apple	36,786	California	6/2/2021 7/17/2021	Early Sept. 2021 October 2021	100%	At least Mon., Tues., and Thurs.	0%
USAA	32,896 (2017)	San Antonio	6/3/2021	July 2021	2%	5 days	98%
NASA	6,000	Marshall Space Flight Center, REDSTONE ARSENAL, Ala.	6/5/2021	June 14, 2021	All employees who must be on-site	5 days	-
Boeing	27,000	Puget Sound, WA	6/5/2021	Mid-July 2021	50%	5 days	<50%
Amazon	1.3M	Seattle	6/10/2021 8/5/2021	Early Sept. 2021 January 3, 2022	Depends on work	3 days	Depends on work
Wells Fargo	260,000	San Francisco	7/16/2021 8/5/2021	September 7, 2021 October 4, 2021	Those in operations and call centers	5 days	-
Lyft	4,675	San Francisco	7/28/2021	February 2022	-	-	-
Coca-Cola	3,100	Atlanta	8/9/2021	mid October 2021	-	-	-

7.3 User Interface and Presentation in Metropia GoEzy app

Metropia's multimodal trip planning supports the following modes of transportation: Drive Alone, Public Transit, Cycling, and Walking. Users can use the transit, walking and cycling navigation that helps them move from their origin to destination. The trip planner's accurate dynamic traveler information is made possible through the backend support of advanced traffic prediction, vehicle navigation, and routing capabilities, and the integration of multiple data sources, such as the General Transit Feed Specification (GTFS) for transit and the General Bicycle Feed Specification (GBFS) for cycle share.

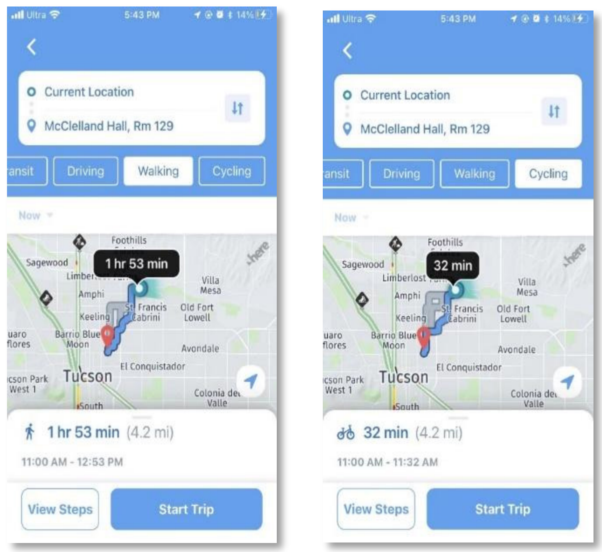


Figure 7-1: Walking and Cycling Planning

For trips made by vehicle, the app provides turn-by-turn navigation and allows customization.

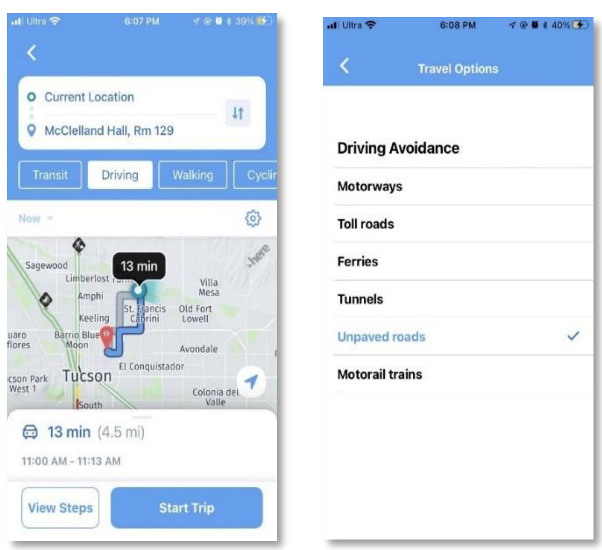


Figure 7-2: Driving Navigation

On GoEzy all mobility service transactions and reward processes are based on a dual virtual currency system. The Mobility Wallet in GoEzy has a wide array of flexible approaches to support both mobility service transactions and incentive campaigns.

Coins are equivalent to cash without expiration and can be used to redeem gift cards. Tokens are issued by a funding entity and have specific application rules; the token feature was not utilized during the Pilot. As previously discussed, in this study, incentive rewards were issued to the users in the form of coins which could be accumulated to redeem for gift cards.

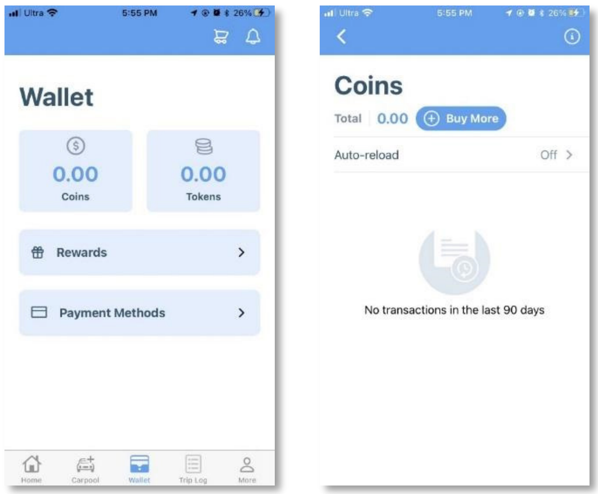


Figure 7-3: Rewards

7.4 Marketing Campaigns Processes and Lessons Learned

This section summarizes the marketing campaigns used to recruit participants to the Pilot. Multiple sets of Facebook ads were deployed until a reasonable number of participants was reached. Table 7-3 provides key metrics for each of the waves of Facebook ads.

Table 7-3: Facebook Campaign Schedule and Outcomes

Campaign Title	Campaign Version	Total weeks	Impress -ions	Down-loads	Total Link Click	Per Link Click	CTR*	User Convers-ion rate**	Per Down-load cost
Facebook awareness I	1.1-1.4	4.6	200,858	96	1,947	$1.52	0.97%	4.93%	$30.77
Facebook awareness II	2.1-2.2	8.4	178,236	73	4,988	$0.65	2.80%	1.46%	$44.22
Facebook awareness III	3.1-3.2	9.9	181,745	9	9,098	$0.54	5.01%	0.10%	$548.71
Facebook Leads	4.0	4.1	36,012	35	338	$4.53	0.94%	10.36%	$43.75
Facebook awareness IIII	5.0	1.0	13,711	3	314	$0.46	2.29%	0.96%	$48.33

In order to strive for a representative sample, the decision was made to avoid enabling persona selection in the Facebook campaign setup and focus solely on geographical boundaries. This approach was chosen to access a broader audience and minimize sampling bias introduced by specific personas. However, it is important to note that Facebook's ads algorithm will initially learn which types of Facebook users are more likely to be interested in the ads, create its own internal persona, and then target similar users to maintain a lower cost-per-click for the clients. This implies that a persona is being formed by Facebook, representing individuals who are interested in participating in the study. Figure 7-4 presents sample statistics from one of the campaigns, showcasing the breakdown of age groups (The x-axis is arranged in the order of 45-54, 55-64, 65+, 35-44, 25-34, 18-24, 13-17) that displayed interest in the survey. The data indicates that the survey attracted individuals primarily in the age range of 30-50, with men being slightly younger than women on average.

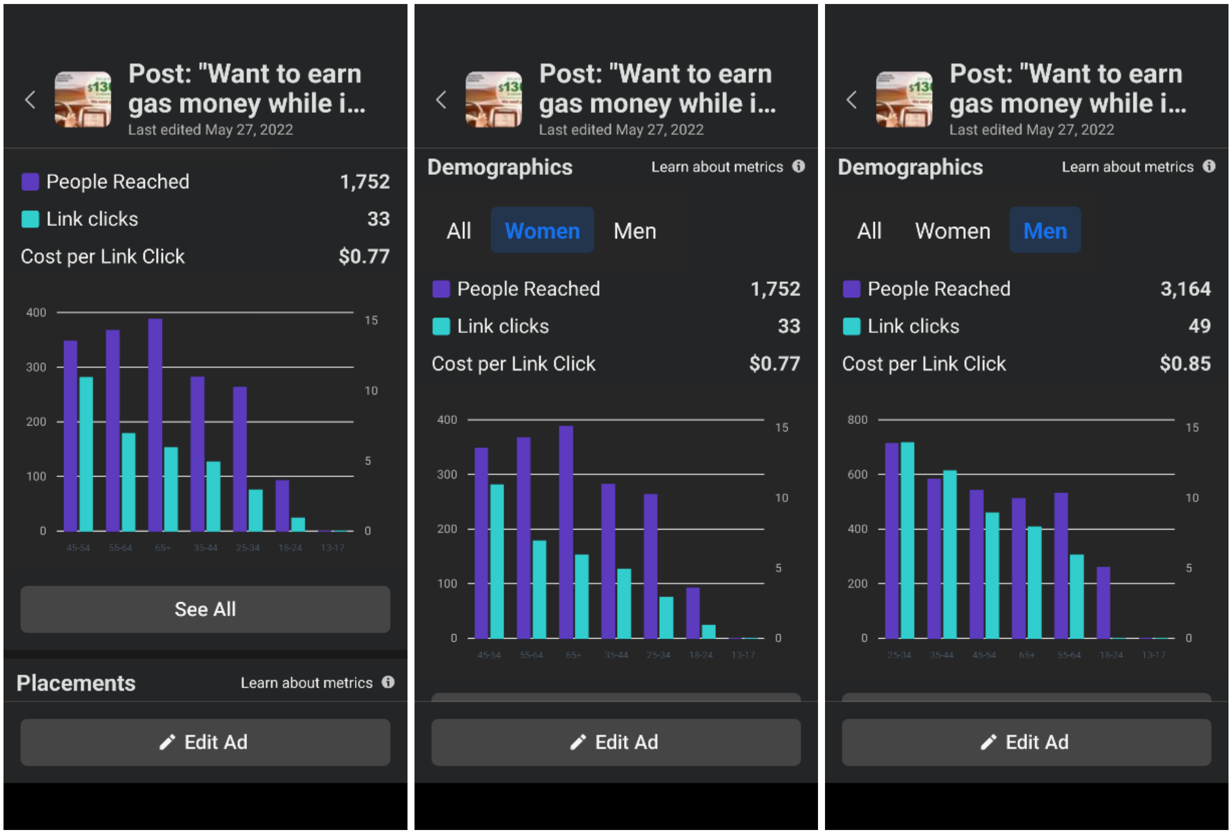


Figure 7-4: Facebook User Demographics Snapshot

7.5 Analytical Methodology

7.5.1 User's Important Locations Process

In the process of mining the travel logs, anonymous user IDs, location IDs, and time interval IDs were used. Notably, the identification of OD pairs did not rely solely on individual longitude and latitude coordinates (Lon./Lat.), but rather leveraged the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) theory to define locations. This approach offered a comprehensive understanding of habitual travel patterns by considering the density and clustering of trips within specific areas.

The identification of GPS clusters and associated central points required a proximity algorithm, and the DBSCAN non-parametric algorithm was used for this purpose (Rahmah and Sitanggang, 2016). The algorithm considered two parameters: a searching radius (ε) around each point and the minimum number (κ) of points required to form a cluster. Finding an appropriate searching radius involved optimization using the data set, such as the k-distance graph (Mullin, n.d.). DBSCAN grouped points in high-density regions, marking outliers for points in low-density areas. The minimum number of points required for a cluster is determined based on domain knowledge and familiarity with the dataset (McFadden, 1973).

7.5.2 Mobility Options Discovery (MOD) Process

The mobility option discovery (MOD) is based on the widely known discrete choice methodology in which the probability of choosing a certain option is governed by the Utility Function.

A traveler is more likely to try a suggested sustainable mode if it is contextually relevant, attractive, and personalized. Metropia's Mobility Options Discovery (MOD) module searched available sustainable modes for each habitual driving trip, calculated the relative attractiveness of each mode using the concept of utility, and suggested the second-best mode option to driving.

For example, as illustrated in Figure 7-5, when a user drives from home (O) to a destination (D) on a Friday evening there may be other travel mode options available such as public transit, walking, cycling or a combination of sustainable mobility options. Based on the characteristics of each mode option (e.g., travel time, number of transfers, etc.), the mode utility and the relative attractiveness of each sustainable mode were calculated as shown in Equation (1). Based on the relative attractiveness, the available modes were ranked and the second-best mode option instead of driving was recommended.

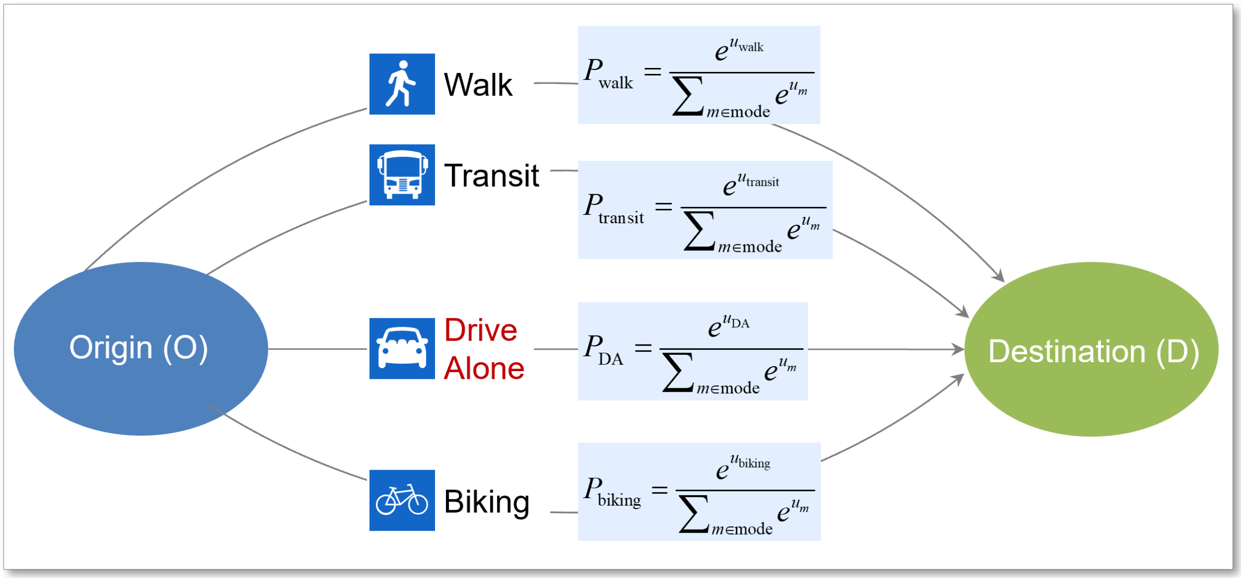


Figure 7-5: Computation of the Second-Best Mode Option Framework

The calculation of the second-best mode option can be expressed in Equation 1 as:

$$U_{\text{transit}} = \alpha_{\text{transit}} + \beta_{\text{WKT,transit}} WKT + \beta_{\text{WT,transit}} WT + \beta_{\text{TT,transit}} TT$$

$$U_{\text{walk}} = \alpha_{\text{walk}} + \beta_{\text{WKT,walk}} WKT$$

$$U_{\text{DA}} = \alpha_{\text{DA}} + \beta_{\text{TT,DA}} TT$$

$$U_{\text{biking}} = \alpha_{\text{biking}} + \beta_{\text{TT,biking}} TT$$

$$P_{\text{transit}} = \frac{e^{u_{\text{transit}}}}{\sum_{m\in\text{mode}} e^{u_m}}$$

$$P_{\text{DA}} = \frac{e^{u_{\text{DA}}}}{\sum_{m\in\text{mode}} e^{u_m}}$$

$$P_{\text{walk}} = \frac{e^{u_{\text{walk}}}}{\sum_{m\in\text{mode}} e^{u_m}}$$

$$P_{\text{biking}} = \frac{e^{u_{\text{biking}}}}{\sum_{m\in\text{mode}} e^{u_m}}$$

Equation (1)

where:

U_{m} represents the deterministic utility of mobility option m (transit, walking, drive alone, cycling) for individual i,

α refers to the constant associated with mobility option m, as estimated from the data,

β represents the estimated coefficients for the explanatory variables (walking time (WKT), waiting time (WT), and in-vehicle time (TT)),

P signifies the relative attractiveness or the probability of a mode being chosen by individual i,

e^{U_m} is the log-transformation of the utility (U_{m}),

$\sum e^{U_m}$ is the summation (log-sum) of the transformed utilities.

7.5.3 Ordinary Least Squares (OLS) Model and Linear Probability Model (LPM)

The Ordinary Least Squares regression model was used to analyze outcomes associated with continuous variables, while the Linear Probability Model was used to analyze the outcomes associated with binary variables. In both Experiments 1 and 2, the explanatory variables represent the treatment conditions (e.g., messages, rewards, etc.) being tested with the outcome variable of interest been the travel mode choice.

The Ordinary Least Squares regression model can be expressed in Equation 1 as:

$$Y = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \varepsilon \qquad \text{Equation (2)}$$

where:

Y is a continuous variable,

$\beta 0$ is the intercept,

$\beta 1, \beta 2, \ldots, \beta n$ represent the magnitude and direction of the relationship between the explanatory variables and the outcome variable

$X1, X2, \ldots, Xn$ are the explanatory variables reflecting the treatments,

ε is the error term.

The Linear Probability Model can be expressed in Equation 3 as:

$$Pr(Y = 1) = \beta 0 + \beta 1X1 + \beta 2X2 + \ldots + \beta nXn \qquad \text{Equation (3)}$$

where:

$Pr(Y = 1)$ represents the probability of the binary outcome being 1,

$\beta 0$ is the intercept,

$\beta 1, \beta 2, \ldots, \beta n$ are the coefficients associated with the explanatory variables X1, X2, …, Xn,

$X1, X2, \ldots, Xn$ are the explanatory variables reflecting the treatments.

7.5.4 Multilevel Logistic Regression (MLR) Model

In addition to the application of the Ordinary Least Squares and Linear Probability Model models, a hierarchical method known as the Multilevel Logistic Regression model is also utilized to examine mode change behavior. This model is distinct from the Ordinary Least Squares and Linear Probability Model, as it is designed to capture relationships and variations within nested data structures (i.e., clustered data under each of multiple units) such as the relationship between individual trips (cluster) and users (units). The Multilevel Logistic Regression consists of three different models that can be used to analyze the data: the trip-level model (lower-level model), the user-level model (upper-level model), and the combined model.

Lower-Level Model

Assuming normally distributed errors, the lower-level model is expressed in Equation 4, where the intercept and regression coefficients associated with the explanatory variables vary across trips. The residual term accounts for lower-level random effects.

$$\hat{Y}_{ij} = \hat{\beta}_{0j} + \beta_{1j}X_{1ij} + \beta_{2j}X_{2ij} + \ldots + \beta_{Qj}X_{Qij}$$
$$Y_{ij} = \beta_{0j} + \sum_{q=1}^{Q}\beta_{qj}X_{qij} + \gamma_{ij},\ Y_{ij} \sim \mathrm{N}\left(\hat{Y}_{ij}, \sigma_{ij}^{2}\right);\ r_{ij} \sim \left(0, \sigma^{2}\right)$$

Equation (4)

where:

Y_{ij} represents a binary dependent variable with values 0 or 1. If 1, then user j took trip i via the suggested non-driving mode,

β_{0j} is the intercept and is assumed to vary across users,

$\sum_{q=1}^{Q}\beta_{1j}$ is the regression coefficient associated with the explanatory variable X_{ij}, and is assumed to vary across users, and ranging from q =1 to Q, where Q is equal to maximum of X_{qij},

γ_{ij} is the residual accounting for lower-level random effects,

X_{qij} refers to the lower-level explanatory variables in the model.

Upper-Level Model

Equation 5 represents the upper-level model proposed by Yannis et al. (2008) and Kreft and de Leeuw (1998), which includes a subscript to account for variation across users.

$$\beta_{0j} = \gamma_{00} + \sum_{s=1}^{S} \gamma_{0s} W_{0j} + \mu_{0j}$$
$$\beta_{qj} = \gamma_{10} + \sum_{q=1}^{Q} \gamma_{qj} W_{qj} + \mu_{1j} \quad \text{Equation (5)}$$

where:

γ_{00} is the intercept denoting the grand mean of β_{0j},

γ_{10} is the intercept denoting the grand mean of β_{sj},

γ_{0s} is the regression coefficient associated with W_{0j},

γ_{qj} is the regression coefficient associated with W_{qj},

W_{0j} is the upper-level characteristics that influence the intercept term in the lower-level model,

W_{qj} is the upper-level characteristic that influences the coefficients of the lower-level variables in the lower-level model,

μ_{0j} is the residual term of β_{0j},

μ_{1j} is the residual term of β_{qj}.

Combined Model

The combined model is expressed by Equation 6, incorporating a logit transformation so that binominal variables can be analyzed as continuous variables.

Multilevel logistic model:

$$Logit(\theta) = \log\left(\frac{P(Y_{ij})}{1-P(Y_{ij})}\right) = \beta_{0j} + \sum_{q=1}^{Q} \beta_{qj} X_{qij} + \gamma_{ij} \quad \text{Equation (6)}$$
$$= \gamma_{00} + \sum_{s=1}^{S} \gamma_{0s} W_{0j} + \sum_{q=1}^{Q} \gamma_{10} X_{qij} + \sum_{q=1}^{Q} \sum_{s=1}^{S} \gamma_{qj} W_{qj} X_{qij} + \mu_{0j} + \sum_{q=1}^{Q} \mu_{1j} X_{qij} + \gamma_{ij}$$

where:

Y_{ij} represents a binary dependent variable with values 0 or 1. If 1, then user j took trip i via the non-driving mode,

$P_{ij}=\left[\exp\left(Y_{ij}\right)/\left(1+\exp\left(Y_{ij}\right)\right)\right]$ is the logit transformation of Y_{ij},

γ_{00} is the intercept denoting the overall mean of Y_{ij},

W_j is the upper-level user characteristic (e.g., user socio-demographic, vehicle characters, user past travel experience),

X_{ij} is the lower-level trip characteristic (e.g., real trip behavior, experiment intervention, rewards),

γ_{0s} is the regression coefficient associated with upper-level characteristics W_j and ranging from s=1 to S, where S is equal to maximum of W_j,

γ_{10} is the regression coefficient associated with lower-level characteristics X_{ij} and ranging from q=1 to Q, where Q is equal to maximum of X_{ij},

γ_{qj} signifies fixed effects, determined by regression coefficients associated with the slope variance, which are explained by a variable at the upper-level (ranging from q=1 to Q),

μ_{0j}, μ_{1j} is a random effect accounting for the random variation at upper-level, where $\mu_j \sim \left(0,\ \tau_{00}\right)$,

γ_{ij} is the lower-level random effect, where $\gamma_{ij} \sim \left(0,\ \sigma^2\right)$.

An Intra Class Correlation (ICC) ratio, defined by Equation 7, is utilized to determine if a single model or a combined model should be used to analyze the data. If the ICC is close to zero, a single level model is sufficient. However, if the ICC is significant, using the Multilevel Logistic Regression is recommended.

$$ICC=\rho=\frac{\sigma_{u_0}^2}{\sigma_{u_0}^2+\sigma^2}$$

Equation (7)

where:

σ^2 is the within-group variance (variance at the trip level for each user),

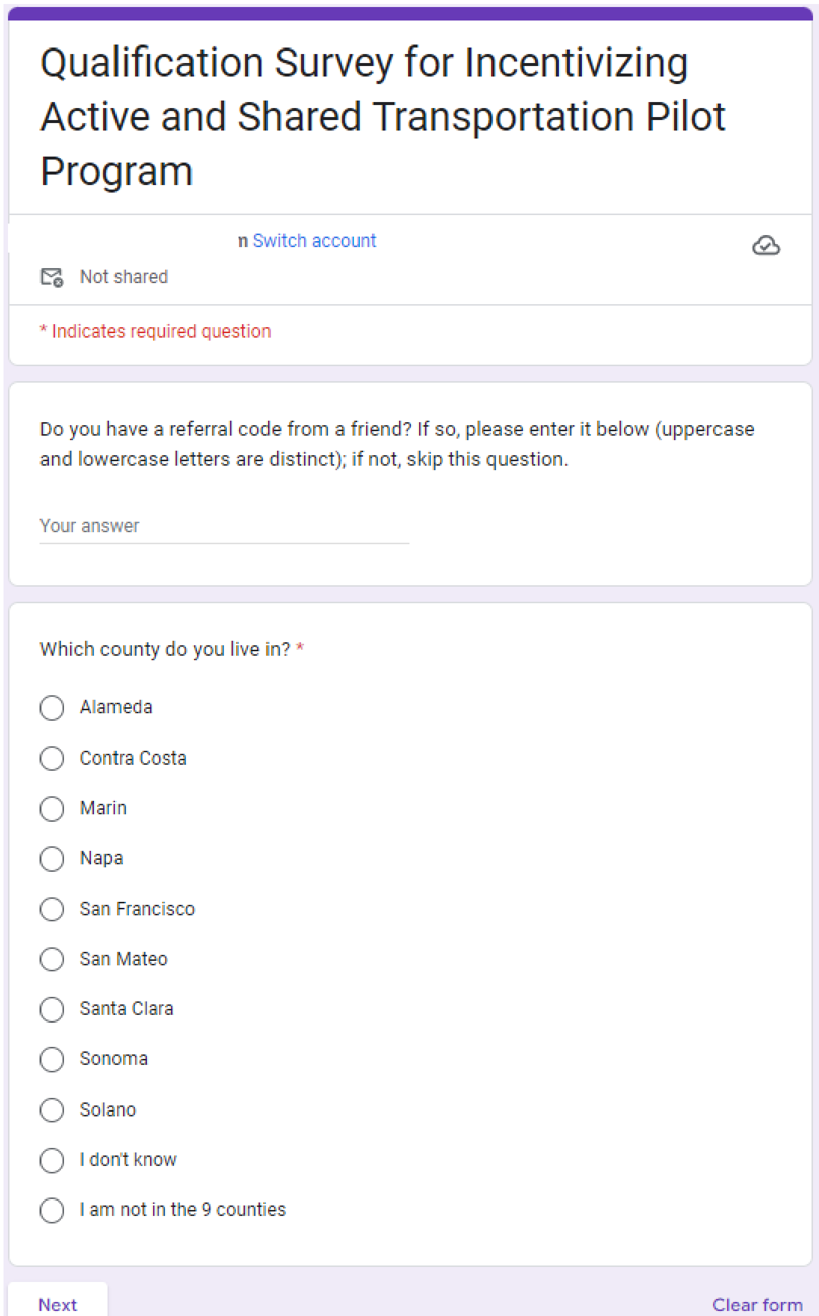
$\sigma_{u_0}^2$ is the between-group variance (variance among users).

The Intra Class Correlation is used to determine the proportion of total variability accounted for by differences among users.

7.6 Survey Questionnaires

Multiple surveys were deployed during the Pilot. Section 7.6.1 presents the survey questionnaire that was used to confirm whether people who had expressed interest in the Pilot met the criteria to participate. Section 7.6.2 presents the survey questionnaire that was used to measure travel concerns and barriers prior to implementing the Pilot.

7.6.1 Qualification Survey



Qualification Survey for Incentivizing Active and Shared Transportation Pilot Program

n Switch account

Not shared

* Indicates required question

Do you have a referral code from a friend? If so, please enter it below (uppercase and lowercase letters are distinct); if not, skip this question.

Your answer

Which county do you live in? *

- Alameda
- Contra Costa
- Marin
- Napa
- San Francisco
- San Mateo
- Santa Clara
- Sonoma
- Solano
- I don't know
- I am not in the 9 counties

Next

Clear form

How many trips do you make in total every week on average? *

- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4
- ◯ 5
- ◯ 6+

Pilot Program Questions

What is the phone number of the smartphone you'll use for this study (That needs to be the same as the one you use for creating the account in the app)? *

Your answer

What is your preferred email for us to send you the participation invitation? *

Your answer

Including yourself, how many people are in your household? *

- ◯ 1
- ◯ 2
- ◯ 3
- ◯ 4+

Do you identify as male, female, non-binary, or another gender identity? *

- ◯ Male
- ◯ Female
- ◯ Non-binary
- ◯ Another gender Identity
- ◯ Refused

In what year were you born? *

- 1945 or earlier
- 1946-1950
- 1951-1955
- 1956-1960
- 1961-1965
- 1966-1970
- 1971-1975
- 1976-1980
- 1981-1985
- 1986-1990
- 1991-1995
- 1996-2002
- Refused

What was your total household income before taxes for X year? Was it: *

- Less than $25,000
- $25,000 to less than 50,000
- $50,000 to less than 75,000
- $75,000 to less than 100,000
- $100,000 to less than 150,000
- $150,000 and over
- Don't Know/Refused

What is the last grade you completed in school? *

- ◯ Some grade school
- ◯ Some high school
- ◯ Graduated High School
- ◯ Technical/Vocational
- ◯ Some College/Less than 4 year degree
- ◯ Graduated College/4 year degree (B-A, Bachelor)
- ◯ Graduate/Professional (M-A, Master, P-h-D, M-B-A, Doctorate)
- ◯ Don't Know/Refused

Which mode of transportation do you use most often? *

- ◯ Car - Solo Travel
- ◯ Carpooling
- ◯ Ride hailing (e.g., Uber/Lyft)
- ◯ Public transportation
- ◯ Cycling
- ◯ Walking
- ◯ Other

Do you have a bicycle available for your daily travel needs? *

- ◯ Yes
- ◯ No

What kind of personal vehicle do you have available for your daily travel needs? *

- ◯ No car available
- ◯ Traditional gasoline/Diesel engine
- ◯ Hybrid
- ◯ Electric or Fuel cell

To what extent do you agree with the following statement: "It is important for me to take steps to combat climate change ." *

- ◯ Strongly disagree
- ◯ Disagree
- ◯ Neither agree nor disagree
- ◯ Agree
- ◯ Strongly agree

How many days per week do you travel to a work or school location outside of your home? *

- ◯ 0
- ◯ 1 - 3
- ◯ 4 - 6
- ◯ 7 and up

Besides work or school, how many trips do you make at least once per week? *

- ◯ 0
- ◯ 1 - 3
- ◯ 4 - 6
- ◯ 7 and up

What is your home zip code? *

Your answer

Figure 7-6: Qualification Survey Questions

7.6.2 [MTC] Travel Behavior and Attitude Survey

7.6.3 Survey Content

We are conducting research to understand traveler behavior and attitudes about transportation. We are interested to hear from you about your daily trip patterns and preferences and how they may have changed since the pandemic. You will be asked to consider your travel choices before and during the pandemic when responding to the following questions. The survey should only take about 15 minutes, and your responses are completely anonymous.

The purpose of this research is to understand travel patterns of individuals in the US and identify the barriers of using more sustainable mobility options.

You can only take the survey once. Questions marked with an asterisk (*) are required.

We really appreciate your input!

[Text] In the next three sections, we'd like you to think about three different trips that you make on a regular basis and answer some questions about how you choose the modes of transportation for those trips from the list below:

- **Personal Vehicle**: drive alone.
- **Carpool**: traveling in your or another's vehicle with 1-3 other people.
- **Vanpool**: traveling in a van with colleagues or classmates within the same organization, most likely provided by your employer.
- **Rideshare Services**: such as Uber, Lyft and/or their shared services Uber Pool, Lyft Line.
- **Carshare:** Rent a car or borrow someone else's car.
- **Public Transit**: such as BART, Bus.
- **Micromobility**: Walk, Bike, Scooter, or Other Shared Modes.

[Question 0] Before we begin, please tell us whether you have used these modes of transportation before.

	Yes	**No**
Personal Vehicle	Radio Button	
Carpool		
Vanpool		
Rideshare Services		
Carshare		
Public Transit		
Micromobility		

[Text] For the next three sections, please think about your current day to day activities.

In the first section, please think about the trip you make the MOST frequently. Now, assume you're about to begin that trip at your regular departure time, and respond to the following questions.

[Question 1.1] What is the reason for this trip?

A. Commuting (work or school)
B. Pick-up/drop-off (family members or friends)
C. Grocery/shopping
D. Dining
E. Leisure (e.g., exercise, sporting event, outdoor activities)
F. Social (visit friends/family)
G. Community/Volunteering or Religious Event
H. Personal business/Errands (medical/dental, bank, post office, etc.)
I. Other_______

[Question 1.2] What time do you usually leave for the trip that you make the most frequently?

A. Midnight (12AM-4:59AM)
B. Morning (5AM-9:59AM)
C. Noon (10AM-12:59PM)
D. Afternoon (1PM-5:59PM)
E. Evening (6PM-11:59PM)

[Question 1.3] When do you often make this trip (multiple selections)?

A. Monday
B. Tuesday
C. Wednesday
D. Thursday
E. Friday
F. Saturday
G. Sunday

[Question 1.4] What is the average travel time for this trip (one-way)?

A. Less than 15 minutes
B. 15-29 minutes
C. 30-44 minutes
D. 45-60 minutes
E. More than 60 minutes

[Question 1.5] How frequently do you make this trip in the same direction?

A. 7+ times per week
B. 4-7 times per week
C. 1-3 times per week
D. 1-3 times per month

[Question 1.6] How flexible is your departure time for this trip (you can leave earlier or later)?

A. Very flexible
B. Somewhat flexible
C. Not flexible

[Question 1.7] Do you usually travel alone or with family members, friends, or colleagues for this trip?

A. Usually alone
B. Sometimes travel with family members, friends, or colleagues
C. Usually with family members, friends, or colleagues

[Question 1.8] What were the mode(s) of transportation that you **used or considered to be potential options** for this trip before the pandemic, and what are the ones you **use or consider to be potential options** now for the trip that you make the most frequently?

Check **all the boxes that apply**.

	Personal Vehicle	**Carpool**	**Vanpool**	**Rideshare Services**	**Carshare**	**Public Transit**	**Micro-mobility**
Before the pandemic	Check						
Currently	Check						

[Question 1.9] What is your **best option** for the trip that you make the most frequently **based on your availability and experience**?

	Personal Vehicle	Carpool	Vanpool	Rideshare Services	Carshare	Public Transit	Micro-mobility
Before the pandemic	Radio button						
Currently	Radio button						

[Question 1.10] What is your **second-best** option for the trip that you make the most frequently **based on your availability and experience**?

	Personal Vehicle	Carpool	Vanpool	Rideshare Services	Carshare	Public Transit	Micro-mobility
Before the pandemic	Radio button						
Currently	Radio button						

[Question 1.11] What is your **third best** option for the trip that you make the most frequently **based on your availability and experience**?

	Personal Vehicle	Carpool	Vanpool	Rideshare Services	Carshare	Public Transit	Micro-mobility
Before the pandemic	Radio button						
Currently	Radio button						

[Question 1.12] Based on your experience or feelings so far, please choose the factors that currently **prevent you from using** the following modes of transportation for the trip that you make the most frequently.

Check all of the boxes that apply.

Notes:

- **Accessibility**: how easy it is to access this mode, including whether you have physical access to it, if the entire journey duration, walking distance, and other factors are acceptable.
- **Reliability**: means whether you feel this mode is running on time.
- **Safety**: whether or not you perceive a personal or road safety related risk when using the mode.
- **Health risk**: whether or not you perceive a health risk when using the mode.
- **Comfort**: how comfortable do you feel when using the mode.
- **Cost**: how satisfied are you with the fare, parking cost, etc.
- **Familiarity**: how familiar are you with the mode, or how easy do you feel to find out how to use the services.

	Not Familiar	Unsatisfied Accessibility	Unsatisfied Reliability	Unsatisfied Safety	Unsatisfied Health Risk	Unsatisfied Comfort	Unsatisfied Cost	None (all satisfied)
Personal Vehicle		Check						
Carpool								
Vanpool								
Rideshare Services								
Carshare								
Public Transit								
Micromobility								

[Question 1.13] How important do you believe the aforementioned factors are when deciding on a mode for the trip that you make the most frequently?

Please rate the factors on a scale of **1 (not very important)** to **3 (very important)**.

Familiarity

Accessibility

Reliability

Safety

Health risk

Comfort

Cost

[Text] In the second section, please think about the trip you make the SECOND MOST frequently. Now, assume you're about to begin that trip at your regular departure time, and respond to the following questions.

[Question 2.1] What is the reason for this trip?

A. Commuting (work or school)
B. Pick-up/drop-off (family members or friends)
C. Grocery/shopping
D. Dining
E. Leisure (e.g., exercise, sporting event, outdoor activities)
F. Social (visit friends/family)
G. Community/Volunteering or Religious Event
H. Personal business/Errands (medical/dental, bank, post office, etc.)
I. Other________

[Question 2.2] What time do you usually leave for the trip that you make the second most frequently?

A. Midnight (12AM-4:59AM)

B. Morning (5AM-9:59AM)

C. Noon (10AM-12:59PM)

D. Afternoon (1PM-5:59PM)

E. Evening (6PM-11:59PM)

[Question 2.3] When do you often make this trip (multiple selections)?

A. Monday

B. Tuesday

C. Wednesday

D. Thursday

E. Friday

F. Saturday

G. Sunday

[Question 2.4] What is the average travel time for this trip (one-way)?

A. Less than 15 minutes

B. 15-29 minutes

C. 30-44 minutes

D. 45-60 minutes

E. More than 60 minutes

[Question 2.5] How frequently do you make this trip in the same direction?

A. 7+ times per week

B. 4-6 times per week

C. 1-3 times per week

D. 1-3 times per month

[Question 2.6] How flexible is your departure time for this trip (you can leave earlier or later)?

A. Very flexible
B. Somewhat flexible
C. Not flexible

[Question 2.7] Do you usually travel alone or with others for this trip?

A. Usually alone
B. Sometimes travel with family members, friends, or colleagues
C. Usually with family members, friends, or colleagues

[Question 2.8] What were the mode(s) of transportation that you **used or considered to be potential options** for this trip before the pandemic, and what are the ones you **use or consider to be potential options** now for the trip that you make the most frequently?

Check **all the boxes that apply**.

	Personal Vehicle	**Carpool**	**Vanpool**	**Rideshare Services**	**Carshare**	**Public Transit**	**Micro-mobility**
Before the pandemic	Check						
Currently	Check						

[Question 2.9] What is your **best option** for the trip that you make the most frequently **based on your availability and experience**?

	Personal Vehicle	**Carpool**	**Vanpool**	**Rideshare Services**	**Carshare**	**Public Transit**	**Micro-mobility**
Before the pandemic	Radio button						
Currently	Radio button						

[Question 2.10] What is your **second-best** option for the trip that you make the most frequently **based on your availability and experience**?

	Personal Vehicle	**Carpool**	**Vanpool**	**Rideshare Services**	**Carshare**	**Public Transit**	**Micro-mobility**
Before the pandemic	Radio button						
Currently	Radio button						

[Question 2.11] What is your **third best** option for the trip that you make the most frequently **based on your availability and experience**?

	Personal Vehicle	**Carpool**	**Vanpool**	**Rideshare Services**	**Carshare**	**Public Transit**	**Micro-mobility**
Before the pandemic	Radio button						
Currently	Radio button						

[Question 2.12] Based on your experience or feelings so far, please choose the factors that currently **prevent you from using** the following modes of transportation for the trip that you make the second most frequently.

Check all of the boxes that apply.

Notes:

- **Accessibility**: how easy it is to access this mode, including whether you have physical access to it, if the entire journey duration, walking distance, and other factors are acceptable.
- **Reliability**: means whether you feel this mode is running on time.
- **Safety**: whether or not you perceive a personal or road safety related risk when using the mode.
- **Health risk**: whether or not you perceive a health risk when using the mode.
- **Comfort**: how comfortable do you feel when using the mode.
- **Cost**: how satisfied are you with the fare, parking cost, etc.
- **Familiarity**: how familiar are you with the mode, or how easy do you feel it is to find out how to use the services?

	Not Familiar	Unsatisfied Accessibility	Unsatisfied Reliability	Unsatisfied Safety	Unsatisfied Health Risk	Unsatisfied Comfort	Unsatisfied Cost	None (all satisfied)
Personal Vehicle		Check						
Carpool								
Vanpool								
Rideshare Services								
Carshare								
Public Transit								
Micromobility								

[Question 2.13] How important do you believe the aforementioned factors are when deciding on a mode for the trip that you make the second most frequently?

Please rate the factors on a scale of **1 (not very important)** to **3 (very important)**.

Familiarity

Accessibility

Reliability

Safety

Health risk

Comfort

Cost

In the third section, please think about the trip you make the THIRD MOST frequently. Now, assume you're about to begin that trip at your regular departure time, and respond to the following questions.

[Question 3.1] What is the reason for this trip?

A. Commuting (work or school)
B. Pick-up/drop-off (family members or friends)
C. Grocery/shopping
D. Dining
E. Leisure (e.g., exercise, sporting event, outdoor activities)
F. Social (visit friends/family)
G. Community/Volunteering or Religious Event
H. Personal business/Errands (medical/dental, bank, post office, etc.)
I. Other_______

[Question 3.2] What time do you usually leave for the trip that you make the third most frequently?

A. Midnight (12AM-4:59AM)
B. Morning (5AM-9:59AM)
C. Noon (10AM-12:59PM)
D. Afternoon (1PM-5:59PM)
E. Evening (6PM-11:59PM)

[Question 3.3] When do you often make this trip (multiple selections)?

A. Monday

B. Tuesday

C. Wednesday

D. Thursday

E. Friday

F. Saturday

G. Sunday

[Question 3.4] What is the average travel time for this trip (one-way)?

A. Less than 15 minutes

B. 15-29 minutes

C. 30-44 minutes

D. 45-60 minutes

E. More than 60 minutes

[Question 3.5] How frequently do you make this trip in the same direction?

A. 7+ times per week

B. 4-6 times per week

C. 1-3 times per week

D. 1-3 times per month

[Question 3.6] How flexible is your departure time for this trip (you can leave earlier or later)?

A. Very flexible

B. Somewhat flexible

C. Not flexible

[Question 3.7] Do you usually travel alone or with others for this trip?

A. Usually alone

B. Sometimes travel with family members, friends, or colleagues

C. Usually with family members, friends, or colleagues

[Question 3.8] What were the mode(s) of transportation that you **used or considered to be potential options** for this trip before the pandemic, and what are the ones you **use or consider to be potential options** now for the trip that you make the most frequently?

Check **all the boxes that apply**.

	Personal Vehicle	**Carpool**	**Vanpool**	**Rideshare Services**	**Carshare**	**Public Transit**	**Micro-mobility**
Before the pandemic	Check						
Currently	Check						

[Question 3.9] What is your **best option** for the trip that you make the most frequently **based on your availability and experience**?

	Personal Vehicle	**Carpool**	**Vanpool**	**Rideshare Services**	**Carshare**	**Public Transit**	**Micro-mobility**
Before the pandemic	Radio button						
Currently	Radio button						

[Question 3.10] What is your **second-best** option for the trip that you make the most frequently **based on your availability and experience**?

	Personal Vehicle	**Carpool**	**Vanpool**	**Rideshare Services**	**Carshare**	**Public Transit**	**Micro-mobility**
Before the pandemic	Radio button						
Currently	Radio button						

[Question 3.11] What is your **third best** option for the trip that you make the most frequently **based on your availability and experience**?

	Personal Vehicle	**Carpool**	**Vanpool**	**Rideshare Services**	**Carshare**	**Public Transit**	**Micro-mobility**
Before the pandemic	Radio button						
Currently	Radio button						

[Question 3.12] Based on your experience or feelings **so far**, please choose the factors that currently **prevent you from using** the following modes of transportation for the trip that you make the third most frequently.

Check all of the boxes that apply.

Notes:

- **Accessibility**: how easy it is to access this mode, including whether you have physical access to it, if the entire journey duration, walking distance, and other factors are acceptable.
- **Reliability**: means whether you feel this mode is running on time.
- **Safety**: whether or not you perceive a personal or road safety related risk when using the mode.
- **Health risk**: whether or not you perceive a health risk when using the mode.
- **Comfort**: how comfortable do you feel when using the mode.
- **Cost**: how satisfied are you with the fare, parking cost, etc.
- **Familiarity**: how familiar are you with the mode, or how easy do you feel to find out how to use the services

	Not Familiar	Unsatisfied Accessibility	Unsatisfied Reliability	Unsatisfied Safety	Unsatisfied Health Risk	Unsatisfied Comfort	Unsatisfied Cost	None (all satisfied)
Personal Vehicle		Check						
Carpool								
Vanpool								
Rideshare Services								
Carshare								
Public Transit								
Micromobility								

[Question 3.13] How important do you believe the aforementioned factors are when deciding on a mode for the trip that you make the third most frequently?

Please rate the factors on a scale of **1 (not very important)** to **3 (very important)**.

Familiarity

Accessibility

Reliability

Safety

Health risk

Comfort

Cost

[Text] In the last section, please answer a few questions about yourself. Remember that all your responses are completely anonymous.

We appreciate your input!

[Question 4.1] How often do you use your personal vehicle if you have one?

A. For most of my trips
B. For some of my trips
C. For very few of my trips
D. I don't use or have a car

[Question 4.2] How many vehicles does your household own or regularly use?

A. 0
B. 1
C. 2
D. 3
E. 4+

[Question 4.3] How often do you use your personal vehicle if you have one?

A. For most of my trips
B. For some of my trips
C. For very few of my trips
D. I don't use or have a car

[Question 4.4] How many bikes does your household own or regularly use?

A. 0
B. 1
C. 2
D. 3+

[Question 4.4] How often do you bike (owned or shared)?

A. For most of my trips
B. For some of my trips
C. For very few of my trips
D. I don't use a bike

[Question 4.5] What is your gender?

A. Man
B. Woman
C. Non-binary
D. Prefer not to answer

[Question 4.6] Are you of Hispanic, Latino, or of Spanish origin?

A. Yes
B. No

[Question 4.7] How would you describe yourself? (choose all that apply)

A. American Indian or Alaska Native
B. Asian
C. Black or African American
D. Native Hawaiian or Other Pacific Islander
E. White

[Question 4.8] What is your age?

A. 18-34
B. 35-44
C. 45-54
D. 55-64
E. 65+

[Question 4.9] How many children under 18 live in your household?

A. 0
B. 1
C. 2
D. 3+
E. Prefer not to answer

[Question 4.10] Which of the following categories best describes your household income in 2020 (in U.S. dollars)?

A. $0
B. $1 to $9,999
C. $10,000 to $24,999
D. $25,000 to 49,999
E. $50,000 to 74,999
F. $75,000 to 99,999
G. $100,000 to 149,999
H. $150,000 and greater
I. Prefer not to answer

[Question 4.11] What is your highest degree or level of school completed?

A. Less than High School
B. High School
C. College
D. Post College

[Question 4.12] Which of the following categories best describes your career field?

A. Architecture and engineering
B. Arts, culture, and entertainment
C. Business, management, and administration
D. Communications
E. Community and social services
F. Education
G. Science and technology
H. Installation, repair, and maintenance
I. Farming, fishing and forestry
J. Government
K. Health and medicine
L. Law and public policy

M. Sales
N. Student
O. Unemployed
P. Retired
Q. Other
R. Prefer not to answer

[Question 4.13] Have you been vaccinated for COVID-19?

A. Partially vaccinated
B. Fully vaccinated
C. No
D. Prefer not to answer

[Question 4.14] How often do you wear a mask or face covering in public indoor environments?

A. Always
B. Often
C. Sometimes
D. Rarely
E. Never

[Question 4.15] How flexible is your work schedule in terms of arrival days and time?

A. Not flexible
B. Somewhat flexible
C. Very flexible

[Question 4.16] What is your current home zip code? _________________

[Question 4.17] What is your current work zip code? _________________

7.7 Participant Characteristics

Figure 7-7 illustrates the participant's residence locations.

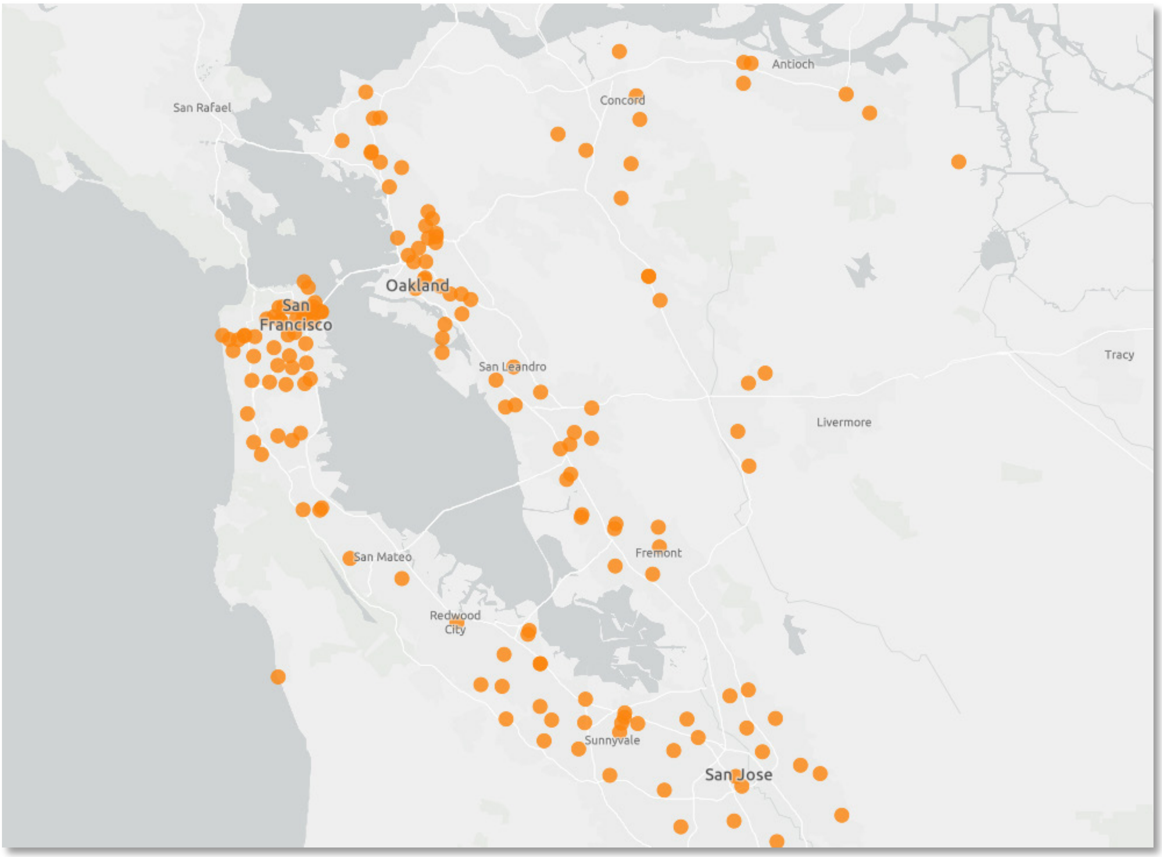


Figure 7-7: Participant Residence Location Distribution

The exploration of socio-demographics and travel patterns in this study served to understand how these elements intersect to inform transportation behavior. Focusing on integral areas, namely demographic profiles, transportation options and vehicle ownership, trip types and frequency, and trip and transit accessibility characteristics, allowed a holistic perspective on transportation decision-making. This data was compiled through the Pilot Qualification Survey shown in Appendix 7.6.1. A summary of the findings is presented below.

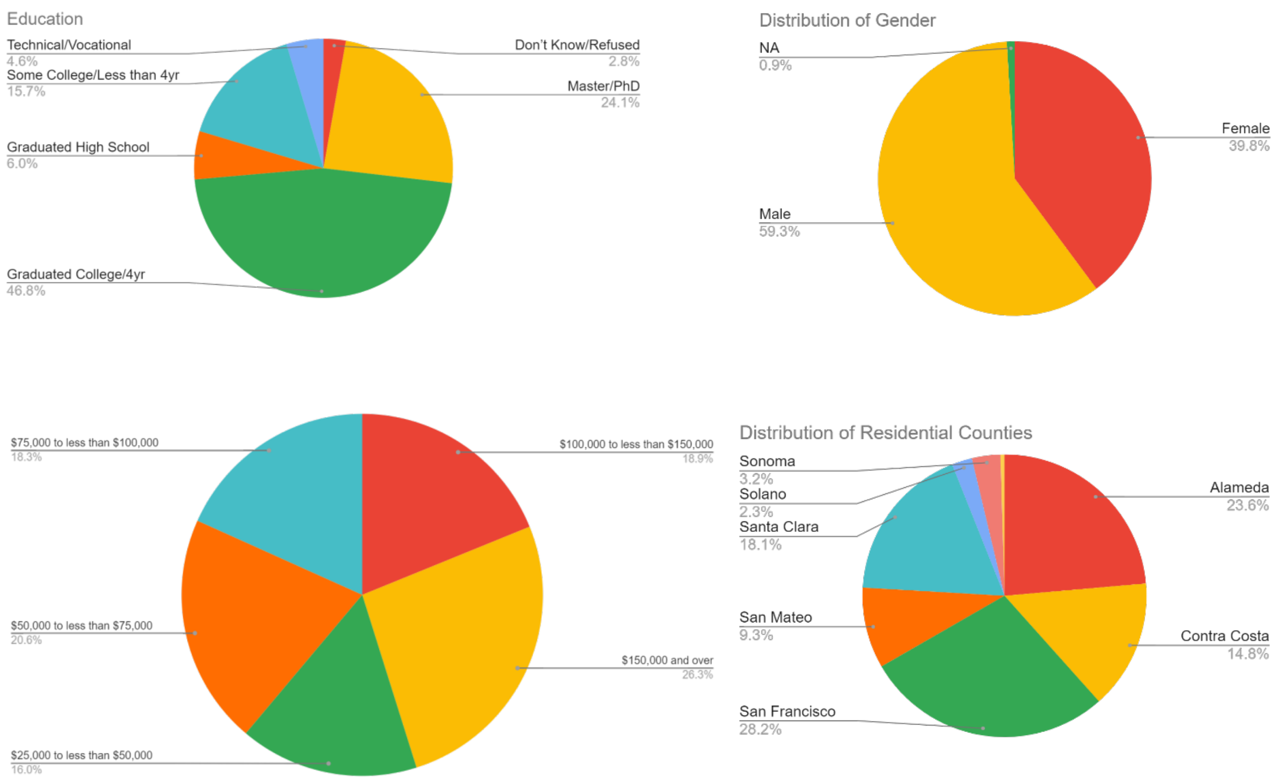


Figure 7-8: Demographic Characteristics of Participants in Survey

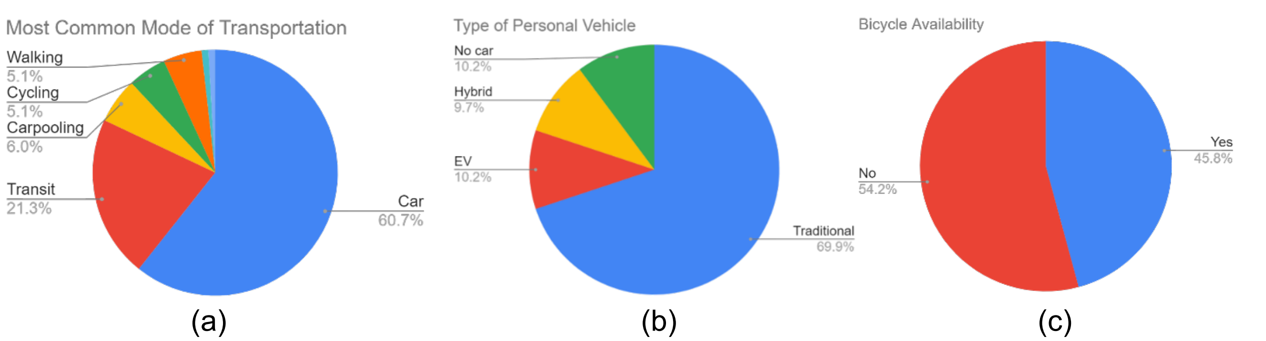


Figure 7-9: Transportation Habits, and Bicycle Availability

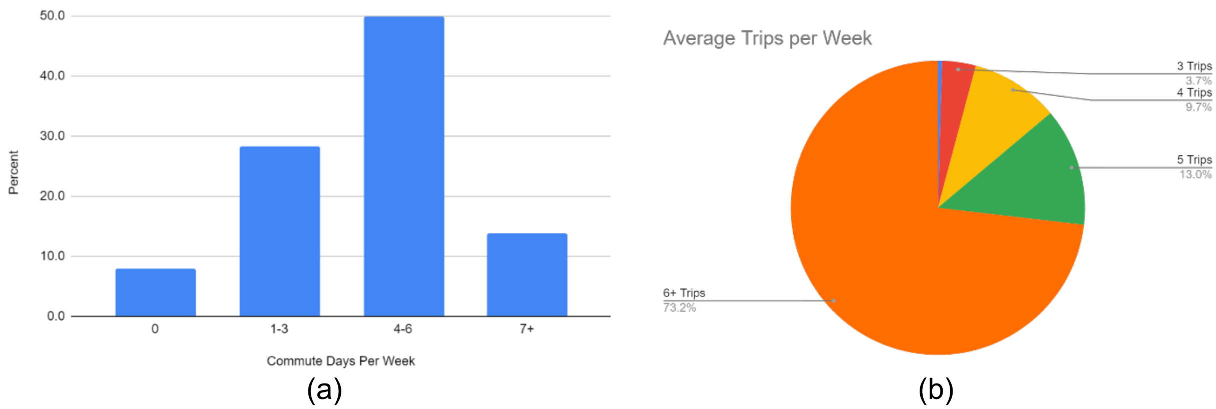


Figure 7-10: Weekly Commuting Days and Trips

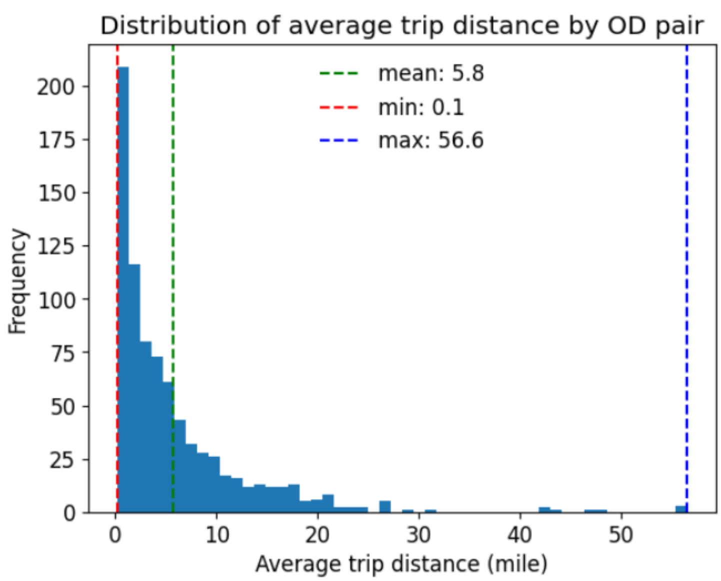


Figure 7-11: Trip Distance Distribution

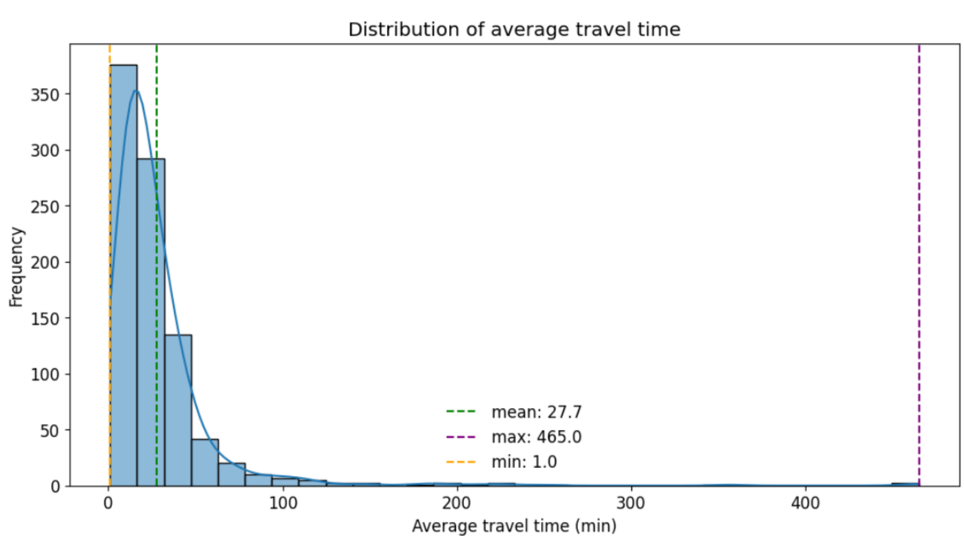


Figure 7-12: Travel Time Distribution

7.8 Experiment 1 Results

Table 7-4: Effect of Treatment on Travel Behavior (relative to the control group)

Treatment	Completed Trip	Completed Trip by Mode				Total Trips within 24 hours	
		Car	Public Transit	Walk	Cycle	Car	Non-car
Lower bound estimate	-0.0090	-0.0101	0.0007	-0.0003	0.0010	-0.2653	0.0066
(p-value)	(0.2977)	(0.2405)	(0.1161)	(0.8391	(0.1847)	(0.5859)	(0.3122)
Upper bound estimate	0.0027	0.0026	0.0004	-0.0009	0.0005	-0.8604*	0.0051
(p-value)	(0.7513)	(0.7587)	(0.2241)	(0.5708)	(0.4469)	(0.09578	(0.47528
Lower bound estimate + green identity	-0.0040	-0.0075	-0.0001	0.0024	0.0013	-0.1767	0.0028
(p-value)	(0.6448)	(0.3896)	(0.3173)	(0.1868)	(0.1133)	(0.7180)	(0.5730)
Upper bound estimate + green identity	-0.0122	-0.0125	-0.0001	0.0001	0.0005	-0.3364	0.0007
(p-value)	(0.1574)	(0.1457)	(0.3173)	(0.9607)	(0.4421)	(0.4690)	(0.9005)
Constant	0.5427	0.5319	0.0001	0.0094	0.0011	16.8428	0.0490
(p-value)	(0.0000)	(0.0000)	(0.3173)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	33,386	33,386	33,386	33,386	33,386	33,386	33,386

Notes: *** = p < 0.01, ** = p < 0.05, * = p < 0.1.

Table 7-5: Effect of Trip Cost Message on Travel Behavior (all treatment groups relative to the control condition)

	Completed Trip	Completed Trip by Mode				Total Trips within 24 hours	
		Car	Public Transit	Walk	Cycle	Car	Non-car
Lower bound estimate	-0.0065	-0.0088	0.0003	0.0010	0.0011*	-0.2213	0.0047
(p value)	(0.3313)	(0.1888)	(0.1652)	(0.4385)	(0.0505)	(0.5588)	(0.2933)
Upper bound estimate	-0.0047	-0.0049	0.0002	-0.004	0.0005	-0.5990*	0.0029
(p value)	(0.4795)	(0.4597)	(0.3200)	(0.7454)	(0.3129)	(0.0960)	(0.5375
Constant	0.5427	0.5319	0.0001	0.0094	0.0011	16.8428	0.0490
(p value)	(0.0000)	(0.0000)	(0.3173)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	33,386	33,386	33,386	33,386	33,386	33,386	33,386

Note: This table presents the differences in travel behavior between the control group and those assigned to upper- and lower-bound treatment conditions. The rows “lower bound estimate” and “upper bound estimate” present the difference in travel behavior relative to the control condition. Half of those allocated to the lower and upper conditions also received a “green identity nudge”.
*** = p < 0.01, ** = p < 0.05, * = p < 0.1.

Table 7-6: Effect of Green Identity Treatment on Travel Behavior

	Completed Trip	Completed Trip by Mode				Total Trips within 24 hours	
		Car	Public Transit	Walk	Cycle	Car	Non-car
Cost with no identity	-0.0031	-0.0037	0.0005**	-0.0006	0.0007	-0.5645	0.0059
(p value)	(0.6419)	(0.58780	(0.0498)	(0.6226	(0.1598)	(0.1241)	(0.2464)
Cost with Green identity	-0.0081	-0.0100	-0.0001	0.0012	0.0090	-0.2573	0.0017
(p value)	(0.2247)	(0.1345)	(0.3173)	(0.3561)	(0.1082)	(0.4883)	(0.6752)
Constant	0.5427	0.5319	0.0010	0.0094	0.0011	16.8428	0.0490
(p value)	(0.0000)	(0.0000)	(0.3173)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	33,386	33,386	33,386	33,386	33,386	33,386	33,386

Note: This table presents the effect of being assigned to the cost with a green identity nudge and the cost without a green identity nudge on travel behavior (relative to the control condition). The "cost with no identity" row presents the differences in travel behavior relative to the control condition.
*** = p < 0.01, ** = p < 0.05, * = p < 0.1.

Table 7-7: Effect of Treatment on Travel Behavior
(all groups relative to the control condition)

	Completed Trip	Completed Trip by Mode				Total Trips within 24 hours	
		Car	Public Transit	Walk	Cycle	Car	Non-car
Treatment	-0.0067	-0.0079	0.0002	0.0003	0.0008*	-0.2152	0.0200***
(p value)	(0.2221)	(0.1484)	(0.1035)	(0.7857)	(0.0550)	(0.4887)	(0.0023)
Constant	0.5427	0.5319	0.0001	0.0094	0.0011	16.8428	0.0490
(p value)	(0.0000)	(0.0000)	(0.3173)	(0.00010)	(0.0000)	(0.0000)	(0.0000)
Observations	33,419	33,419	33,419	33,419	33,419	33,419	33,419

Note: This table presents the effect of being assigned to any treatment condition on travel behavior. The "treatment" row presents the differences in travel behavior relative to the control condition.
*** = p < 0.01, ** = p < 0.05, * = p < 0.1.

Table 7-8: Effect of Treatment on Travel Behavior for Flexible and Non-Flexible Travelers

Treatment	Completed Trip	Completed Trip by Mode				Total Trips within 24 hours	
		Car	Public Transit	Walk	Cycle	Car	Non-car
Received treatment message x non-flexible travelers	0.0012	0.0007	0.0003*	-0.0001	0.0004	0.3790	0.0072
(p value)	(0.8600)	(0.9148)	(0.0833)	(0.8540)	(0.3097)	(0.2512)	(0.1351)
Is a flexible traveler	-0.0601***	-0.0875***	0.0002	0.0266***	0.0009	0.9517*	0.1088***
(p value)	(0.0000)	(0.0000)	(0.3173)	(0.0000)	(0.1825)	(0.0861)	(0.0000)
Received treatment x flexible traveler	-0.0216*	-0.0234**	-0.0001	0.0005	0.0012	-1.8309**	0.3744**
(p value)	(0.0635)	(0.0462)	(0.8124)	(0.8842)	(0.2749)	(0.0155)	(0.0418)
Constant	0.5635***	0.5612***	-0.0000	0.0011***	0.0009***	16.6083***	0.0151***
(p value)	(0.0000)	(0.0000)	(1.0000)	(0.0030)	(0.0016)	(0.0000)	(0.0000)
Observations	33,266	33,266	33,266	33,266	33,266	33,266	33,266

Note: *** = p < 0.01, ** = p < 0.05, * = p < 0.1.

7.9 Experiment 2 Results

7.9.1 Data Description and Structure

Figure 7-13 illustrates the variables associated with both Experiments 1 and 2 that are identified as key influencing factors for behavior change. These variables can be classified either as trip-level or user-level data. The trip-level data pertains to the specific characteristics of each trip, while user-level data focuses on the user attributes, collected from the Pilot Qualification Survey.

The analysis for Experiment 1 was conducted using a total of 33,386 planned non-habitual driving trips, undertaken by 157 users. The Ordinary Least Squares and Linear Probability Model analysis for Experiment 2 is based on 69,384 predicted upcoming habitual driving trips, while the Multilevel Logistic Regression model specifically focused on analyzing the treatment effect of completed trips using the suggested sustainable mode, which consists of 7,433 completed habitual driving trips, undertaken by 59 users. Further analysis suggested that the average interval between registration and the commencement of the first trip was approximately 2.5 days. It was observed that among the users who became active, an average duration of 9.1 days elapsed before the formation of a habitual trip.

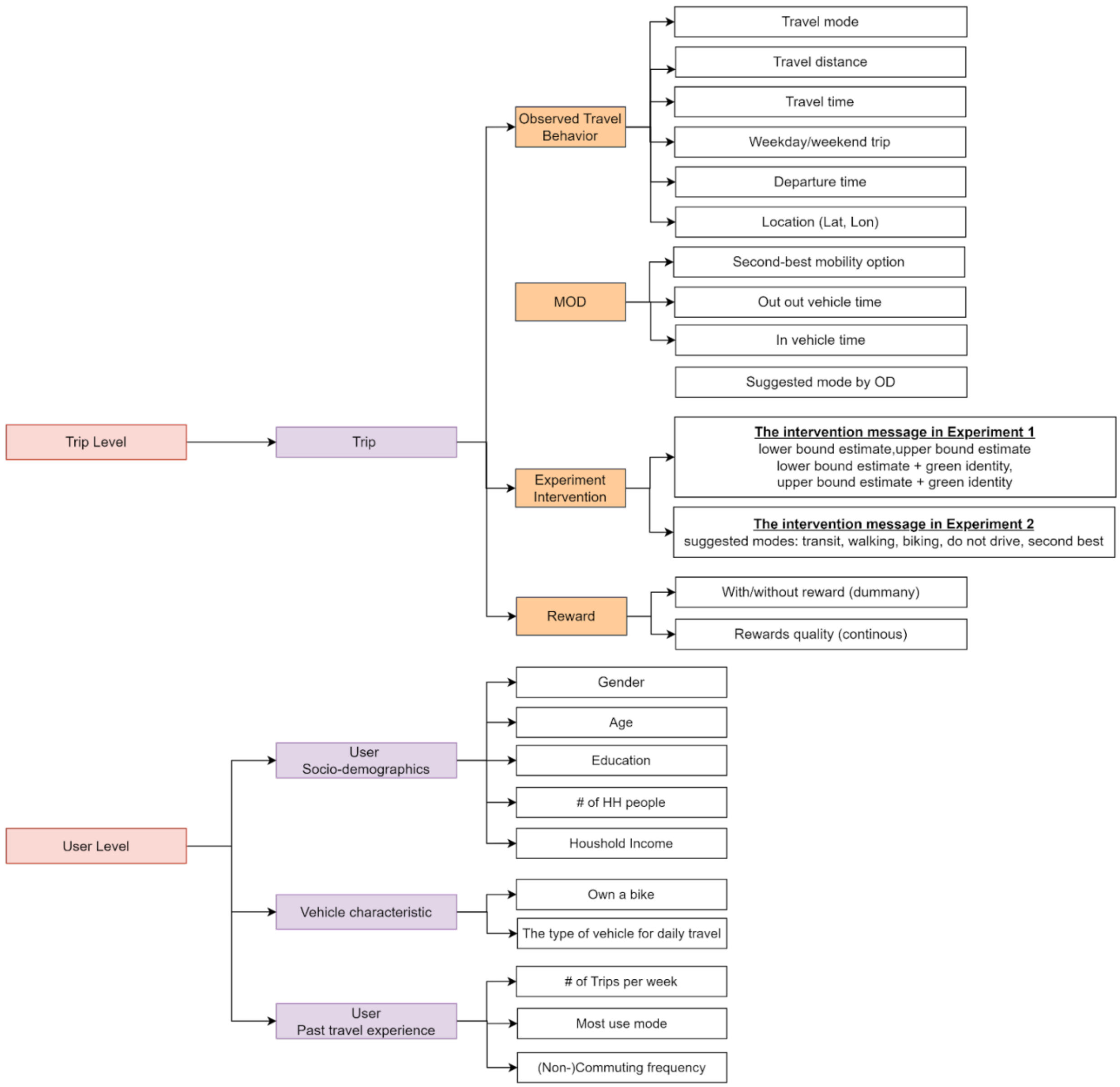


Figure 7-13: Trip-Level and User-Level Variables

7.9.2 Multilevel Logistic Regression Model Analysis

The Multilevel Logistic Regression model utilizes two variable categories referred to as "Lower-Level Variables" and "Upper-Level Variables", organized into two distinct levels, as depicted in Figure 7-14.

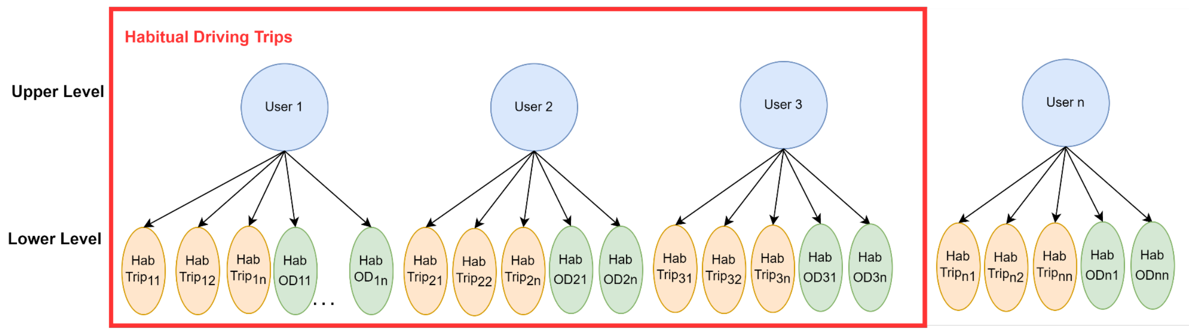


Figure 7-14: Experiment 2: Trip-Level and User-Level Characteristics

Lower-Level variables reflect trip attributes and how they relate to the associated mode of transportation. They may vary on a trip-by-trip basis but provide insights into the minutiae of each trip, helping to paint a detailed picture of transportation behavior at a micro level. Upper-Level variables focus on user-specific attributes and reflect characteristics such as bicycle availability or residential location. These variables provide a macro perspective, offering insights into broader behavioral trends influenced by users' attributes. Table 7-9 provides a summary of the variables used in the analysis. The upper-level reflects fifty-nine (59) users and the lower-level reflects 7,433 completed habitual driving trips by these users. For the purposes of the Multilevel Logistic Regression analysis, the individual completed habitual driving trips were associated with their important location clusters and assigned a single Origin (O), reflecting the origin cluster and Destinations (D), reflecting the destination cluster, forming the habitual OD pair referenced in the narrative below.

The Multilevel Logistic Regression model was estimated using the maximum likelihood method with the dependent variable indicating whether the habitual driving OD pair had changed to a non-driving mode after users received the suggested mode tile. To that extent, if one of the completed habitual driving trips associated with a habitual OD pair was taken by a non-driving mode after the user received the treatment then the habitual OD pair was assigned a value of 1, otherwise it is zero. The analysis aimed to identify the factors that influenced the likelihood of mode change for the OD pair.

The Multilevel Logistic Regression demonstrated a superior fit to the data, as supported by the residual intra-class correlation coefficient (ICC), a key statistic used to evaluate the performance of multilevel models (Hilbe, 2009). The ICC value was 0.763.[20] indicating a strong level of similarity within groups (i.e., users) as well as a significant influence of user-level factors on the mode change behavior after they received the suggested transportation mode tile.

[20] The associated p-value was 0.000, indicating that ICC coefficient was statistically significantly different from zero.

Table 7-10 summarizes the Multilevel Logistic Regression model explanatory variable coefficients as well as, the associated p-values and Odds Ratio.[21]

Table 7-9: Descriptions of Variables

Variables		Description	Mean	Min	Max	Type
Lower-Level Variables						
Trip Characteristics and Tile Interaction Item	Dis_walk	Variable is set to 1 if the travel distance of the origin-destination (OD) pair is less than 3 miles and a walking tile is received.	0.190	0	1	dummy
	dis_bke	Variable is set to 1 if the travel distance of the origin-destination (OD) pair falls between 3 and 10 miles and a cycling tile is received.	0.078	0	1	dummy
Trip Characteristics	OD_TT	Variable is set to 1 if the average travel time between the origin-destination (OD) pair is less than 5 minutes.	0.989	0	1	dummy
	weekday_trip	Variable is set to 1 if the trip is made between Monday and Friday.	0.885	0	1	dummy
Interaction between Trip and Suggestion Tile	peak_trip_walktile	Variable represents the percentage of total received walking tiles during peak hours out of all the tiles received.	0.064	0	1	conti
	peak_trip_cycletile	Variable represents the percentage of total received cycling tiles during peak hours out of all the tiles received.	0.062	0	1	conti
Suggestion Tile With or Without Second-Best Tile	reward_walktile	Variable represents the count of randomly distributed walking tile recommendations with rewards that users have received.	13.534	0	69	conti
	reward_tilecycle	Variable represents the count of randomly distributed cycling tile recommendations with rewards that users have received.	16.989	0	58	conti
	reward_SB_PTtile	Variable represents the count of second-best tile recommendations with rewards that users have received.	1.096	1	4.4	conti
Interaction between Suggestion Tile and Incentive	PT_IVTT_ comp	Variable is set to 1 when the additional in-vehicle travel time (IVTT) of transit is less than 15 minutes with reward, and the reward can be converted into compensation of $40 per hour.	0.252	0	7.4	conti
	PT_OVTT_comp	Variable is set to 1 when the out-of-vehicle travel time (OVTT) of transit is less than 15 minutes, and the transit tile suggestions with rewards can be converted into compensation of $40 per hour.	0.002	0	1	dummy

[21] Odds Ratio is commonly used in hierarchical logistic models to assess the effects of different explanatory variables on the outcome variable. For example, an odds ratio of 60 implies that for every unit increase in the explanatory variable, the odds of the outcome occurring are 60 times higher.

Table 7-9: Descriptions of Variables

Variables		Description	Mean	Min	Max	Type
	PT_OVTT	Variable is set to 1 when the out-of-vehicle travel time for choosing public transit as the suggested mode exceeds 40 minutes.	0.214	0	1	dummy
Upper-Level Variables						
User characteristics	Cycle_ availability	Variable is set to 1 when the bicycle is availability.	0.621	0	1	dummy
	Contra Costa	Variable is set to 1 when the user resides in the Contra Costa County	0.135	0	1	dummy
	San Francisco	Variable is set to 1 when the user resides in San Francisco County.	0.051	0	1	dummy
	Santa Clara	Variable is set to 1 when the user resides in the Santa Clara County, restricted to the zip code 94024.	0.007	0	1	dummy

Table 7-10: Multilevel Logistic Regression Results

Variables	Variable	Coef.	p-value	Odds Ratio
Trip-Level Variables				
Trip Characteristics and Tile Interaction Item	Dis_walk	0.383	0.000***	1.47
	dis_bke	1.320	0.000***	3.74
Trip Characteristics	OD_TT	4.095	0.002***	60.01
	weekday_trip	0.357	0.006***	1.43
Interaction between Trip and Suggestion Tile	peak_trip_walktile	2.635	0.000***	13.94
	peak_trip_cycletile	-0.327	0.145	0.72
Suggested Tile With or Without Second-Best Tile	reward_walktile	0.046	0.000***	1.05
	reward_cycletile	0.042	0.000***	1.04
	reward_SB_PTtile	0.658	0.000***	1.93
Interaction between Suggestion Tile and Incentive	PT_IVTT_comp	0.613	0.000***	1.85
	PT_OVTT_comp	1.217	0.094*	3.38
	PT_OVTT	-1.016	0.000***	0.36
User Level Variables				
User characteristics	Cycle_ availability	6.175	0.000***	480.62
User Location	Contra Costa	5.398	0.006***	221.05
	San Francisco	2.834	0.093*	17.01
	Santa Clara	6.619	0.078*	748.90
Constant		-16.284	2.128	0.000
N			7,433	
Variance of the random effects (with parameters)			10.572	0.000

Table 7-10: Multilevel Logistic Regression Results

Variables	Variable	Coef.	p-value	Odds Ratio
τ00			3.251	0.000
ρ(ICC value)			0.763	0.000
Log-likelihood of the null model			-2,736.299	
Log-likelihood			-2,334.061	

Note: *** = p < 0.01, ** = p < 0.05, * = p < 0.1

7.9.3 Ordinary Least Squares Regression and Linear Probability Model Analysis

Table 7-11: Interaction Effects of Treatment and Age

	Completed Trip	Completed Trip by Mode					
		Car	Non-car	Public Transit	Walk	Cycle	Intermodal
Treatment=1	0.0033	0.0035	-0.0001	-0.0002	0.0005	-0.0004*	-0.0002
(p-value)	(0.4048)	(0.3634)	(0.8056)	(0.1573)	(0.2969)	(0.0993)	(0.3093)
37 to 56	0.1411***	0.1053***	0.0322***	-0.0002	0.0293***	0.0031***	0.0033***
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.1573)	(0.0000)	(0.0000)	(0.0000)
57 to 76	0.0656***	0.0524***	0.0094***	-0.0002	0.0102***	-0.0005**	0.0037***
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.1573)	(0.0000)	(0.0253)	(0.0007)
Treatment=1 # 37 to 56	-0.0067	-0.0109**	0.0043**	0.0003	0.0027	0.0014**	0.0001
(p-value)	(0.2347)	(0.0422)	(0.0224)	(0.1001)	(0.1323)	(0.0384)	(0.8797)
Treatment=1 # 57 to 76	-0.0028	0.0008	-0.0016	0.0002	-0.0022	0.0004*	-0.0019
(p-value)	(0.7633)	(0.9312)	(0.5273)	(0.1573)	(0.3650)	(0.0993)	(0.1623)
Constant	0.0754***	0.0734***	0.0016***	0.0002	0.0009***	0.0005**	0.0003*
(p-value)	(0.0000)	(0.0000)	(0.0001)	(0.1573)	(0.0047)	(0.0253)	(0.0832)
Observations	67,693	67,693	67,693	67,693	67,693	67,693	67,693
R-squared	0.026	0.016	0.011	0.000	0.009	0.001	0.001

Note: *** = p < 0.01, ** = p < 0.05, * = p < 0.1.

Table 7-12: Effect of Flexible User and Treatments

	Completed Trip	Completed Trip by Mode					
		Car	Non-car	Public Transit	Walk	Cycle	Intermodal
Treatment=1	-0.0025	-0.0024	0.0001	-0.0001	-0.0001	0.0003	-0.0001
(p-value)	(0.4955)	(0.4909)	(0.9228)	(0.1573)	(0.8486)	(0.3695)	(0.6414)
Flexible user - different mode in first two weeks=1	0.1275***	0.0066	0.1076***	-0.0001	0.0973***	0.0103***	0.0124***
(p-value)	(0.0000)	(0.2681)	(0.0000)	(0.1573)	(0.0000)	(0.0000)	(0.0000)
Treatment=1 # Flexible user- different mode in first two weeks=1	0.0085	-0.0018	0.0124*	0.0003	0.0108*	0.0013	-0.0017
(p-value)	(0.3930)	(0.8243)	(0.0589)	(0.1641)	(0.0840)	(0.5615)	(0.4634)
Constant	0.1745***	0.1661***	0.0072***	0.0001	0.0059***	0.0012***	0.0012***
(p-value)	(0.0000)	(0.0000)	(0.0000)	(0.1573)	(0.0000)	(0.0000)	(0.0000)
Observations	53,551	53,551	53,551	53,551	53,551	53,551	53,551

Note: *** = p < 0.01, ** = p < 0.05, * = p < 0.1.

Table 7-13: Composite Treatment Effects

	Completed Trip	Completed Trip by Mode					
		Car	Not Car	Public Transit	Walk	Cycle	Intermodal
Composite Treatment	-0.0020	-0.0037	0.0022*	-0.0000	0.0017	0.0004	-0.0004
(p-value)	(0.4901)	(0.1599)	(0.0600)	(0.5604)	(0.1074)	(0.2494)	(0.3458)
Constant	0.1692	0.1440	0.0223	0.0001	0.0199	0.0024	0.0028
(p-value)	(0.0000)	(0.0000)	(0.1573)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	69,384	69,384	69,384	69,384	69,384	69,384	69,384
R-squared	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: *** = p < 0.01, ** = p < 0.05, * = p < 0.1.

Table 7-14: Effect of Assignment to Different Treatment Conditions on Travel Behavior (relative to the control condition)

	Completed Trip	Completed Trip by Mode					
		Car	Non-car	Public Transit	Walk	Cycle	Intermodal
Public Transit	0.0016	0.0005	0.0014	0.0001	0.0009	0.0005	-0.0002
(p value)	(0.7482)	(0.9195)	(0.4652)	(0.5686)	(0.6318)	(0.4917)	(0.7773)
Walking	-0.0089*	-0.0069	-0.0009	-0.0001	-0.0002	-0.0006	-0.0010*
(p value)	(0.0653)	(0.1286)	(0.6517)	(0.1573)	(0.9306)	(0.2514)	(0.0742)
Cycling	0.0014	0.0003	0.0018	-0.0001	0.0013	0.0006	-0.0007
(p value)	(0.7717)	(0.9396)	(0.3595)	(0.1573)	(0.5009)	(0.3731)	(0.2147)
Do not drive	-0.0013	-0.0044	0.0038*	-0.0001	0.0023	0.0016*	-0.0007
(p value)	(0.7980)	(-0.3398)	(0.0657)	(0.1573)	(0.2252)	(0.522)	(0.2417)
Second best	-0.0027	-0.0083*	0.0046**	-0.0001	0.0044**	0.0002	0.0009
(p value)	(0.5840)	(0.0674)	(0.0291)	(0.1573)	(0.0271)	(0.7298)	(0.2636)
Control group	0.1692***	0.1440***	0.0223***	0.0001	0.0199***	0.0024***	0.0028***
(p value)	(0.0000)	(0.0000)	(0.0000)	(0.1573)	(0.0000)	(0.0000)	(0.0000)
Observations	69,384	69,384	69,384	69,384	69,384	69,384	69,384

Note: This table displays the effect of being assigned to one of the treatment conditions (e.g., "cycle" or "second best" message) on participants' travel behavior. The "public transit", ..., and "second best" rows represent the difference between the control group and the respective treatment groups.
*** = p < 0.01, ** = p < 0.05, * = p < 0.1.

Table 7-15: Treatment Effects on Only Car Feasible Trips

	Completed Trip	Completed Trip by Mode					
		Car	Non-car	Public Transit	Walk	Cycle	Intermodal
Received treatment	-0.0028	-0.0038	0.0012	-0.0000	0.0011	0.00017	-0.0003
(p value)	(0.3753)	(0.2078)	(0.3496)	(0.5606)	(0.3774)	(0.6947)	(-0.3927)
Constant	0.1710***	0.1460***	0.0227***	0.0001	0.0202***	0.0024***	0.0019***
(p value)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	55,176	55,176	55,176	55,176	55,176	55,176	55,176

Note: *** = p < 0.01, ** = p < 0.05, * = p < 0.1.

Table 7-16: Effect of Incentive Amount

	Completed Trip	Completed Trip by Mode			Total Trips by within 24 hours	
		Car	Public Transit	Cycle	Car	Non-car
incentive_amount_shown	0.0074	0.0094	-0.0018	-0.0014	-0.0004	0.0002
(p value)	(1.00)	(1.34)	(-0.59)	(-0.60)	(-0.19)	(0.17)
Constant	0.295***	0.232***	0.0480***	0.0320***	0.0160***	0.0127***
(p value)	(15.08)	(12.63)	(5.62)	(4.69)	(3.03)	(3.19)
Observations	1,513	1,513	1,513	1,513	1,513	1,513

Note: *** = p < 0.01, ** = p < 0.05, * = p < 0.1.

Table 7-17: Effect of Varying Amount of Incentive

	Completed Trip	Completed Trip by Mode				
		Car	Non-car	Walk	Cycle	Intermodal
Incentive Amount = $1.00	-0.0287	-0.0299	-0.0038	0.0038	-0.0076	0.0089
(p-value)	(0.4302)	(0.3777)	(0.8180)	(0.7776)	(0.4571)	(0.2858)
Incentive Amount = $2.00	-0.0038	-0.0084	0.0089	0.0098	-0.0009	-0.0004
(p-value)	(0.9258)	(0.8244)	(0.6450)	(0.5241)	(0.9372)	(0.9605)
Incentive Amount = $3.00	0.0462	0.0282	-0.0025	0.0049	-0.0074	0.0244*
(p-value)	(0.2711)	(0.4734)	(0.8924)	(0.7464)	(0.5037)	(0.0512)
Incentive Amount = $4.00	-0.0014	0.0245	-0.0142	-0.0077	-0.0065	-0.0078
(p-value)	(0.9763)	(0.5878)	(0.4683)	(0.6105)	(0.6095)	(0.1568)
Incentive Amount = $5.00	0.0982*	0.1059**	-0.0045	-0.0019	-0.0026	0.0007
(p-value)	(0.0681)	(0.0412)	(0.8436)	(0.9139)	(0.8609)	(0.9477)
Incentive Amount = $6.00	-0.1321**	-0.0931	-0.0273	-0.0273***	0.0001	-0.0078
(p-value)	(0.0300)	(0.1073)	(0.2469)	(0.0075)	(0.9971)	(0.1568)
Constant	0.3086***	0.2500***	0.0469***	0.0273***	0.0195**	0.0078
(p-value)	(0.0000)	(0.0000)	(0.0004)	(0.0075)	(0.0244)	(0.1568)
Observations	1,513	1,513	1,513	1,513	1,513	1,513
R-squared	0.009	0.009	0.001	0.002	0.001	0.008

Note: *** = p < 0.01, ** = p < 0.05, * = p < 0.1.