INCENTIVIZING ACTIVE AND SHARED TRAVEL PILOT PROGRAM

Task 7.1 Evaluation Analysis Technical Memo

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Prepared for:

METROPOLITAN TRANSPORTATION COMMISSION

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EXECUTIVE SUMMARY

The Metropolitan Transportation Commission's (MTC) Climate Initiatives Program identified in Plan Bay Area 2050 (PBA 2050) invests in strategies that reduce the region's greenhouse gas (GHG) emissions by reducing vehicle miles traveled (VMT). Plan Bay Area 2050, the region's Sustainable Communities Strategy and long-range transportation plan, charts the course for the future of the nine-county San Francisco Bay Area. One of the main goals of PBA 2050 is to reduce VMT through strategies that encourage travelers to use active and shared transportation options rather than driving alone, including walking, cycling, taking transit, and carsharing.

MTC's Incentivizing Active and Shared Travel Pilot Program ("Pilot") focuses on how to use behavioral economics and experimentation to achieve the goals laid out in Plan Bay Area 2050. The Pilot seeks to understand behavior and the tradeoffs people face when deciding between traveling in single-occupancy vehicles (SOV) and sustainable mobility options (e.g., public transit and cycling) for any type of habitual[1] trip, including shopping, medical/dental appointments, and going to the gym or work. In contrast to some previous efforts that have used behavioral prompts to influence travel behavior, this Pilot recognizes that not all travelers are good targets for a behavior change campaign. Indeed, one key objective of this Pilot was to first identify individuals whose behavior and habits are open to change and then to evaluate different interventions to determine how to effectively achieve long-lasting shifts in travel choices that result in VMT and GHG emissions reductions.

Shifting transportation behavior away from single-occupancy vehicles towards more sustainable travel methods is a complex process that requires understanding travelers' knowledge, priorities, and motivations, along with providing habitual drivers with active and shared transportation options that are attractive. A critical component of understanding what influences a traveler's choice requires analyzing the traveler's socio-demographics, temporal and spatial activity characteristics, and the transportation landscape conditions and constraints influencing the mobility option decision. Quantitative data analysis aims to understand the audience's travel patterns and preferred modes of transportation, while qualitative data analysis (such as interviews with MTC and other regional agencies to gain insight into the local transportation context) complements the quantitative data and aims to understand the reasons underlying the audiences' travel behaviors from both a demand and supply perspective.

As part of the process, it is important to base decisions not solely on the findings or conclusions drawn from each data source but also on a comparative analysis of data sets. To that extent, the Pilot undertook two behavioral experiments, where various monetary and non-monetary interventions were promoted to engage individuals in behavior change. The first experiment targeted planned non-habitual driving trips and examined the efficacy of informational nudges to encourage travel behavior change towards a sustainable mode. The second experiment targeted predicted upcoming habitual driving Origin-Destination (OD) pairs that utilized monetary incentives (redeemable for gift cards) in addition to informative nudges to influence participants' mode shift behavior. As travelers were recruited,

[1] A habitual trip is defined as a repeated trip between an origin and destination, initiated during a specified departure time interval.

Metropia's GoEzy mobile app, available for downloading from the Apple and Google stores, was the main medium for the experiment implementation.

The evaluation indicated that message-only interventions had no significant overall effect on participants' travel mode choices. However, segment analysis revealed that participants who were identified as being more 'flexible' in their travel modes (i.e., those who traveled using more than one mode in the first week of the study) were more responsive to the interventions. These participants were significantly less likely to complete trips by car after receiving an intervention and were more likely to use non-car travel modes in the twenty-four hours following the intervention.

The evaluation of the effects of monetary incentive and message interventions on predicted upcoming habitual driving trips indicated that tailored interventions, offering a second-best option[2] based on an individual's environment and trip details, were more effective than generic mode-specific messages. The analysis of the out-of-vehicle travel time (OVTT[3]) and in-vehicle travel time (IVTT[4]), both specifically for transit and for the second-best mode revealed their significant impact on transportation choices. When incentives are used, and IVTT for transit is kept under 15 minutes, a notable change in habitual mode choices occurs. However, if OVTT for transit exceeds 40 minutes, incentives do not generate a significant effect. The analysis highlighted the significant influence of personalized recommendations on transportation choices, with individuals being nearly 14 times more likely to choose walking during peak hours when receiving a recommendation. The analysis emphasized the importance of second-best choice recommendations, which notably influenced individuals to select public transit as their sustainable option. Additionally, compensation for extra travel time was found to play a role in individuals' decisions to opt for public transit. Furthermore, suggesting walking for trips under 3 miles and cycling for trips between 3 and 10 miles had a significant effect on changing habitual mode choices. The presence of bicycles in townships, as well as in Contra Costa, San Francisco, and Santa Clara Counties, positively influenced individuals' willingness to adopt sustainable transportation. These findings highlight the potential for sustainable spatial planning and transportation policies to promote more sustainable travel behaviors.

These findings, albeit intriguing, should be interpreted with caution. The study was conducted during the COVID-19 pandemic, which may have influenced the number of data points collected and, potentially, participants' travel behaviors.

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[2] Defined as the best appealing sustainable mode option next to driving.

[3] Out-of-vehicle travel time (OVTT) refers to the amount of time a traveler spends outside of a vehicle during a trip, such as waiting for a bus or train, transferring between modes, or walking to their final destination.

[4] In-vehicle travel time (IVTT) refers to amount of time inside modes like car, cycle or in this context, specifically transit.

1 INTRODUCTION

The Metropolitan Transportation Commission's (MTC) Climate Initiatives Program, as identified in Plan Bay Area 2050 (PBA 2050), is investing 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, cycling, transit, and carsharing.

MTC’s Incentivizing Active and Shared Travel Pilot Program (“Pilot”), a Climate Initiatives strategy, applies the latest behavioral economics theories and practices to explore effective strategies to trigger and sustain behavior change that reduce VMT and GHGs. The Pilot seeks to understand behavior and the tradeoffs between driving in a single occupancy vehicle (SOV) and utilizing a sustainable mobility option (e.g., public transit, cycling, 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 aims to identify how to sustain changes in travel behavior.

Shifting transportation behavior away from single-occupancy vehicles towards more sustainable travel methods is a complex process that requires understanding travelers' knowledge, priorities, and motivations, along with providing habitual drivers with active and shared transportation options that are attractive. A critical component of understanding what influences a traveler’s choice requires analyzing the traveler's socio-demographics, temporal and spatial activity characteristics, and the transportation landscape conditions and constraints influencing the mobility option decision. Quantitative data analysis aims to understand the audience’s travel patterns and preferred modes of transportation, while qualitative data analysis (such as interviews with MTC and other regional agencies to gain insight into the local transportation context) complements the quantitative data and aims to understand the reasons underlying the audiences’ travel behaviors from both a demand and supply perspective.

As part of the process, it is important to base decisions not solely on the findings or conclusions drawn from each data source but also on a comparative analysis of data sets. To that extent, the Pilot undertook two behavioral experiments, where various monetary and non-monetary interventions were promoted to engage individuals in behavior change. The first experiment targeted planned non-habitual driving trips and examined the efficacy of informational nudges to encourage travel behavior change towards a sustainable mode. The second experiment targeted predicted upcoming habitual driving Origin-Destination (OD) pairs that utilized monetary incentives (redeemable for gift cards) in addition to informative nudges to influence participants' mode shift behavior. As travelers were recruited, Metropia’s GoEzy mobile app, available for downloading from the Apple and Google stores, was the main medium for the experiment implementation.

The purpose of this report is to provide a comprehensive technical overview of the two Behavioral Experiments conducted and an evaluation analysis for the Pilot. The report is organized as follows. Chapter 2 establishes the methodological framework, detailing the differentiation between habitual and non-habitual trips, introducing the concept of the habitual OD, the elements of the Experiments Design, and the importance of Statistical Power in Randomized Controlled Trials (RCTs). In addition, Chapter 2 delves into the Ordinary Least Squares (OLS) and Multilevel Logistic Regression (MLR), utilized in the

Experiment analyses. Chapter 3 introduces the data structure and presents a comprehensive summary of the socio-demographics and travel patterns of the participants, focusing on key areas that are closely linked to transportation behavior and user characteristics. Chapter 4 presents the analysis for Experiment 1 using the OLS model, while Chapter 5 presents the analysis for Experiment 2 using both the OLS and MLR methodologies. Chapter 6 provides a summary of the overall findings. Appendix A includes the Qualification Survey, while Appendix B, Appendix C, and Appendix D provide tables with additional OLS and MLR model results.

2 METHODOLOGY

2.1 Definition of Habitual versus Non-Habitual Trips

Recurring congestion is defined as the congestion caused by routine traffic volumes operating in a typical environment and is associated with “recurring” activities such as commuting to work or school. In this context, a key question of interest is how strategies can change travel choices formed as habits, where a habit or habitual choice is defined as choosing to perform a behavior without deliberation (Ronis et al. 1989; Gärling & Garvill 1993).

Therefore, a habitual trip is defined as the recurring pattern of travel choice behavior, signified by a consistent Origin-Destination (OD) pair and departure time interval (T), undertaken on different days. Meanwhile, the "habitual OD" refers to the aggregation of many such habitual trips. Conversely, any travel that doesn't conform to this pattern is classified as a non-habitual trip. Behavior changes pertaining to non-habitual travel choices could impact recurring congestion in the short-term, but for a lasting solution, behavior changes need to focus on altering habitual trip mobility options (i.e., altering habits).

2.1.1 User’s Important Locations

Real world recurring travel behavior does not always happen at a specific time and the associated trip ends may not always be the exact same address. For example, while a user commutes from home to work every day the origin could be a different on-street parking space every day in the same neighborhood or the user’s own home. In a similar fashion, the destination could be the user’s work place every day or one day the coffee shop and the other day the dry cleaners around the corner of the workplace, before ending at the actual workplace. Furthermore, the GPS coordinates associated with a specific origin or destination could exhibit a temporal variation in the longitude and latitude values recorded in the backend servers. To that extent, an origin or a destination, although spatially anchored, may be associated with several GPS points in close proximity.

To that extent, habitual trips are associated with a departure time interval (i.e., T=15 min) and with “Important Locations,” defined as the central point of clusters formed by GPS points, as illustrated in Figure 2-1. For example, all individual trips between Important Location A and Important Location D and departing at T, will be identified as the same habitual trip, and locations A and D would be defined as the habitual origin and destination (OD pair). Furthermore, since travel behavior between weekdays and weekend is generally different, trips are associated with a flag identifying whether the trip took place during a weekday or the weekend. As such, the underlying patterns and factors influencing travel behavior could be mined and analyzed.

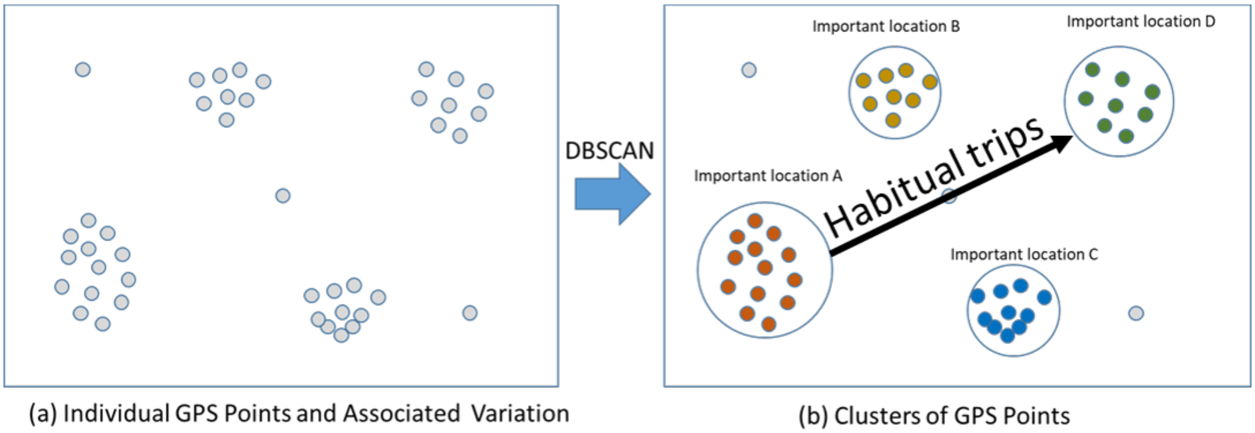

Figure 2-1: Illustration of Defining User's Important Location
(Source: Metropia)

The mining process on the travel logs includes anonymous user IDs, location IDs, and time interval IDs. It is worth noting that the identification of OD pairs does not rely solely on individual longitude and latitude coordinates (Lon./Lat.), but rather utilizes the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) theory to define locations. This approach enables a more comprehensive understanding of habitual travel patterns and behavior by considering the density and clustering of trips within specific areas.

Identifying the GPS clusters and the associated central points requires a proximity algorithm and the DBSCAN (Rahmah and Sitanggang 2016) non-parametric algorithm is used for this purpose. The algorithm considers two parameters: a searching radius (ε) around each point and the minimum number (κ) of points required for shaping a cluster. If the searching radius is too small, many of the GPS points will not be clustered, while if the searching radius is large, clusters will merge, and the majority of the GPS points will be in one cluster.

The searching radius can be determined using an optimization algorithm according to the data set (e.g., k-distance graph) (Mullin n.d.). DBSCAN groups points that are close to each other in high-density regions and marks as outliers the points that are in low-density regions. The minimum number of points required for a cluster is based on domain knowledge and familiarity with the dataset (McFadden 1973). For the Pilot, the values for the minimum number of GPS points and the searching radius of the cluster are defined as 2 points and 656.168 ft., respectively.

2.2 Assessing Minimum Detectable Effect (MDE) and Statistical Power in Randomized Controlled Trials (RCTs)

Both Experiments were designed as Randomized Controlled Trials (RCTs), which are considered the 'gold standard' of experimental design, since RCTs allow researchers to evaluate the causal relationship between the explanatory variable(s) and the outcomes of interest. Participants are randomly assigned to either the treatment group(s) or the control group, which is considered as a counterfactual to the treatment Group(s). The outcomes are then compared across all groups to determine if there is a statistically significant difference between the control and treatment groups and among the treatment groups.

When designing an experiment, it is important to ensure that it adequately detects a “true effect” and the probability associated with it. The Minimum Detectable Effect (MDE) refers to the smallest effect that is meaningful to detect. For example, it would not be helpful to detect an effect of 2% or less, because such a small effect would not be cost effective to pursue for a given intervention. In addition to the MDE value, the concept of “statistical power”, “power” or “sensitivity” of the experiment is relevant. Power refers to the likelihood of detecting a true effect from an explanatory variable if indeed such an effect exists. In other words, the greater the statistical power, the more likely to pick up on an effect. Typically, a power of 80% or greater is considered sufficient and indicates that if the same experiment was conducted 100 times, an effect would be identified 80 times. For the Pilot program a 3% MDE value and an 80% “power” values were established, which are typical for studies of this kind based on existing literature (lucilemouse 2016; Bloom 1995). Establishing the MDE value at 3% does not mean that detecting an effect at 2% or lower is not possible, but rather the strength of the association would be lower and therefore not a strong finding. In addition, “power” is used in determining the sample size required, given the number of interventions to be trialed.

2.3 Mobility Options Discovery (MOD)

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 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 2-2, 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 deterministic utility of each travel mode, represented as U_{m}, are calculated as shown in Equation (1). This utility encompasses several factors that dictate its attractiveness.

For transit, two key factors play a pivotal role in determining its attractiveness: walking time to the transit point and the waiting time for transit. As represented in the utility functions, both walking time (WKT) and waiting time (WT) are essential determinants in the decision to use transit. A shorter walking time or waiting period enhances the appeal of transit as a preferred mode. Consequently, the utility functions imply that as these times decrease, transit becomes an increasingly attractive option. It's common in transportation studies to combine these two components into a single metric known as OVTT (out-of-vehicle travel time), which captures the time spent outside the vehicle while accessing or waiting for transit. Moreover, in-vehicle time (TT) is another intrinsic component of this utility function, further elucidating its influence on the decision-making process.

For other modes such as walking, driving alone, and biking, the utility is primarily influenced by the in-vehicle or travel time. The coefficients β associated with each of these times reflect their relative significance in the attractiveness of each mode.

Based on the relative attractiveness, the available modes are ranked and the second-best mode option, instead of driving, is recommended. It's pivotal to note that the attractiveness or the probability of a mode being chosen by an individual, represented by P , is derived from the log transformation of the utility, indicating the mathematical relationship between a mode's inherent characteristics and its selection probability.

To sum it up, the utility functions presented shed light on the myriad of factors that shape the attractiveness of each mode. By understanding and integrating these, the easier it is to anticipate user choices and promote sustainable mobility options.

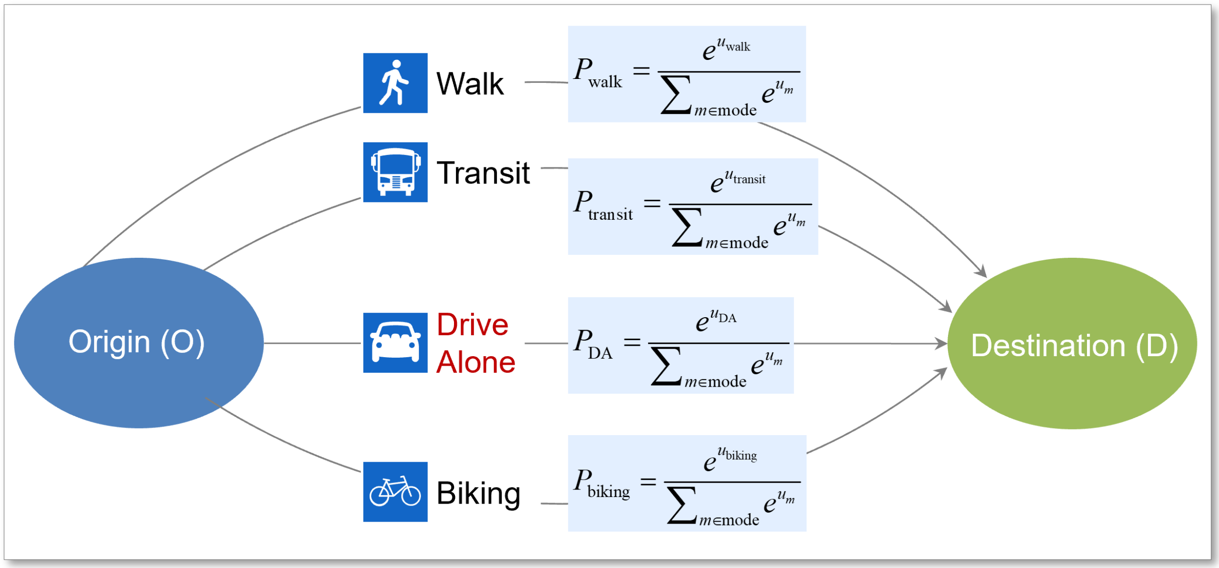

Figure 2-2: Visualization of the 2nd-Best Mode Option Framework

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

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

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

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

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

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

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

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

$$P_{\text{biking}} = \frac{e^{u_{\text{biking}}}}{\sum_{m \in \text{mode}} e^{u_m}} \qquad \text{Equation (1)}$$

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.

In this study, a mode is considered appealing when the probability P is greater than or equal to 10%.

2.4 Suggestion Tiles

Rather than pursuing a radical immediate behavior change from travelers, Metropia's behavior engine powered by **MODE®**, (Mobility Options Discovery and Engagement) supports a communication mechanism, referred to as Suggestion Tiles, to warm the identified target individuals up to the proposed sustainable option. Suggestion Tile sample screenshots are illustrated in Figure 2-3 to Figure 2-5 and a description is provided below.

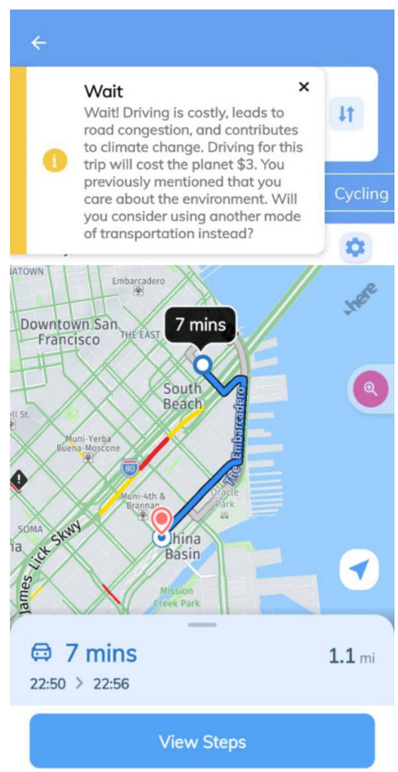

Figure 2-3: Conceptual Illustration of Experiment 1 Messages

- **Information (Info) tile**: This type of 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**: This type of 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 his or her commute time more efficiently.
- **Action tile with a variable monetary incentive**: This type of tile works like the action tile with the bonus that if the user takes 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.

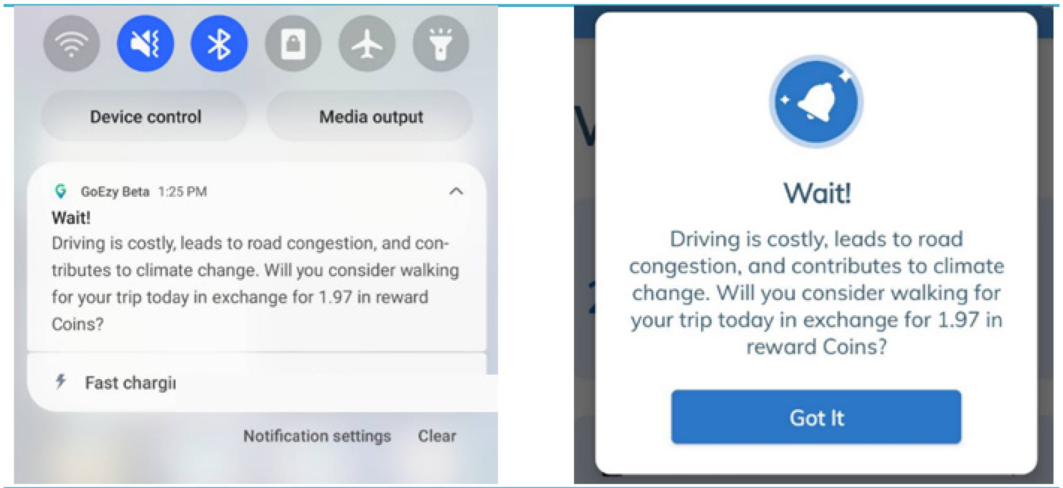

Figure 2-4: Info Tile Example of Experiment 2 Messages

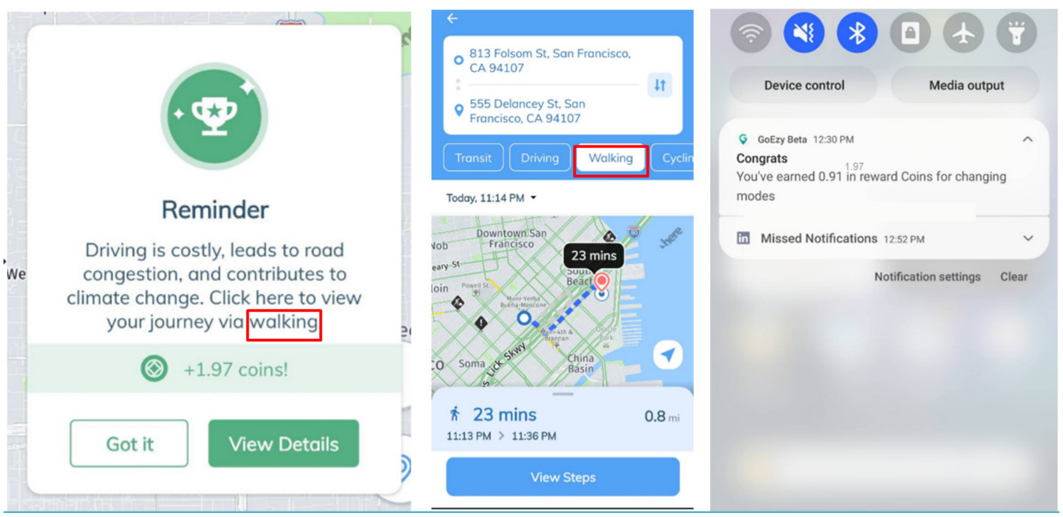

Figure 2-5: Action Tile Example of Experiment 2 Messages

2.5 Modeling Approaches

In this study, the principal modeling approaches are Linear Probability Model (LPM) and Logistic Regression (LR). The LPM model was chosen because of its simplicity and ease of interpretation. The coefficients of the model directly indicate the change in the probability of the event for a one-unit change in the corresponding independent variable.

Some common use cases for LPMs include:

- **Program Evaluation**: LPMs are used to evaluate the impact of a treatment or intervention on a binary outcome. For example, assessing the effectiveness of an educational program on students' graduation rates.
- **Public Policy Analysis**: LPMs are applied in public policy research to study the impact of policy changes on binary outcomes, such as the effect of a new law on voting behavior.
- **Marketing and Advertising**: LPMs are employed to understand consumer behavior and predict the probability of a customer responding to a marketing campaign or advertisement.

Logistic Regression (LR) is a versatile statistical method widely used in various fields for modeling binary or categorical outcomes. Some common use cases for LR include:

- **Marketing Analytics**: Predicting whether a customer will purchase a product or subscribe to a service based on their demographics, browsing behavior, or purchase history.
- **Customer Churn Prediction**: Identifying customers who are likely to churn (stop using a service) based on their usage patterns and engagement behavior.
- **Recommender Systems**: Predicting user preferences in recommendation systems to suggest personalized content or products.

The main differences between an LPM and LR are in their underlying assumptions and the way they handle binary outcome data.

Linear Probability Model (LPM):

- **Assumptions**: LPM assumes a linear relationship between the independent variables and the probability of the binary outcome. It assumes that changes in the independent variables lead to constant changes in the probability of the event occurring.
- **Probability Range**: LPM directly predicts probabilities of the binary outcome and can produce values outside the valid probability range of 0 to 1. For example, predicted probabilities can be negative or greater than 1, which is not meaningful in a probability context.
- **Interpretation**: The coefficients in an LPM represent the change in the probability of the event occurring for a one-unit change in the corresponding independent variable. The interpretation of coefficients is straightforward.

Logistic Regression (LR):

- **Assumptions**: LR does not assume a linear relationship between the independent variables and the probability of the binary outcome. Instead, it uses the logistic function (sigmoid curve) to model the relationship, which ensures that the predicted probabilities always fall within the valid probability range of 0 to 1.
- **Probability Range**: LR models the log-odds (logit) of the event occurring, and then transforms it back to probabilities using the logistic function. This ensures that the predicted probabilities are always within the valid range.
- **Interpretation**: In LR, the coefficients represent the change in the log-odds (logit) of the event occurring for a one-unit change in the corresponding independent variable. Interpreting the coefficients requires converting them back to probabilities using the logistic function.

In this study, both LPM and LR were employed. The LPM was used to provide an intuitive depiction of statistical relationships between treatments and the likelihood of behavior change. The LR model increased the modeling flexibility to explore more complex relationships between variables and how these variables affect behavior change. More details about both models are discussed in the subsections below.

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

In the following analysis, different statistical models were implemented to elucidate the outcomes of the experiments, each chosen according to the specific nature of the data being examined. For outcomes involving continuous variables, which are capable of assuming any value within a range, the OLS regression model was utilized. This model is instrumental in delineating the effects of varying treatment conditions, such as messages or rewards, on these continuous outcomes. Conversely, for outcomes related to binary variables, characterized by having only two possible values (e.g., 'yes' or 'no'), the Linear Probability Model (LPM) was employed. This model is adept at examining the influence of different treatment conditions on binary decision-making processes. In both Experiments 1 and 2, the explanatory variables encompassed the treatment conditions under investigation, with the focal point being the assessment of how these treatments influenced travel mode choice.

The OLS regression model can be expressed in Equation 2 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 LPM can be expressed in Equation 3 as:

$Pr(Y = 1) = \beta 0 + \beta 1X1 + \beta 2X2 + ... + \beta nXn$ Equation (3)

where:

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

$\beta 0$ is the intercept,

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

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

2.5.2 Multilevel Logistic Regression (MLR) Model

In the analysis, beyond the implementation of Ordinary Least Squares (OLS) and Linear Probability Model (LPM), the Multilevel Logistic Regression (MLR) model is also employed to investigate mode change behavior. The MLR, an advanced form of Logistic Regression (LR), is designed to explore interactive relationships within hierarchical data structures, such as the interplay between individual trips (the clusters) and users (the units). This model is adept at handling data where observations are nested within multiple layers, accounting for potential dependencies and variations across these layers.

The overarching structure of the MLR model can be summarized as follows: After a detailed process of iterative model specification and calibration, the finalized MLR framework comprises three distinct but interconnected models. These include the trip-level model, which operates at the lower level, focusing on the specifics of individual trips; the user-level model, positioned at the upper level, concentrating on the characteristics and behaviors of users; and the combined model, which integrates insights from both the trip and user levels to provide a comprehensive analysis.

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.

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

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.

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

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:

$$Logit(\theta) = \log\left(\frac{P(Y_{ij})}{1-P(Y_{ij})}\right) = \beta_{0j} + \sum_{q=1}^{Q}\beta_{qj}X_{qij} + \gamma_{ij}$$

$$= \gamma_{00} + \sum_{s=1}^{S}\gamma_{0s}W_{0j} + \sum_{q=1}^{Q}\gamma_{10}X_{qij} + \sum_{q=1}^{Q}\sum_{s=1}^{S}\gamma_{qj}W_{qj}X_{qij} + \mu_{0j} + \sum_{q=1}^{Q}\mu_{1j}X_{qij} + \gamma_{ij}$$

Equation (6)

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,

$P_{ij} = \left[\exp(Y_{ij}) / \left(1+\exp(Y_{ij})\right)\right]$ 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 $\mu_j \sim (0,\ \tau_{00})$,

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

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 MLR 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 ICC is used to determine the proportion of total variability accounted for by differences among users.

3 EXPERIMENTAL DATA DESCRIPTION, STRUCTURE AND ANALYSIS

3.1 Data Description and Structure

Figure 3-1 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 included in Appendix A.

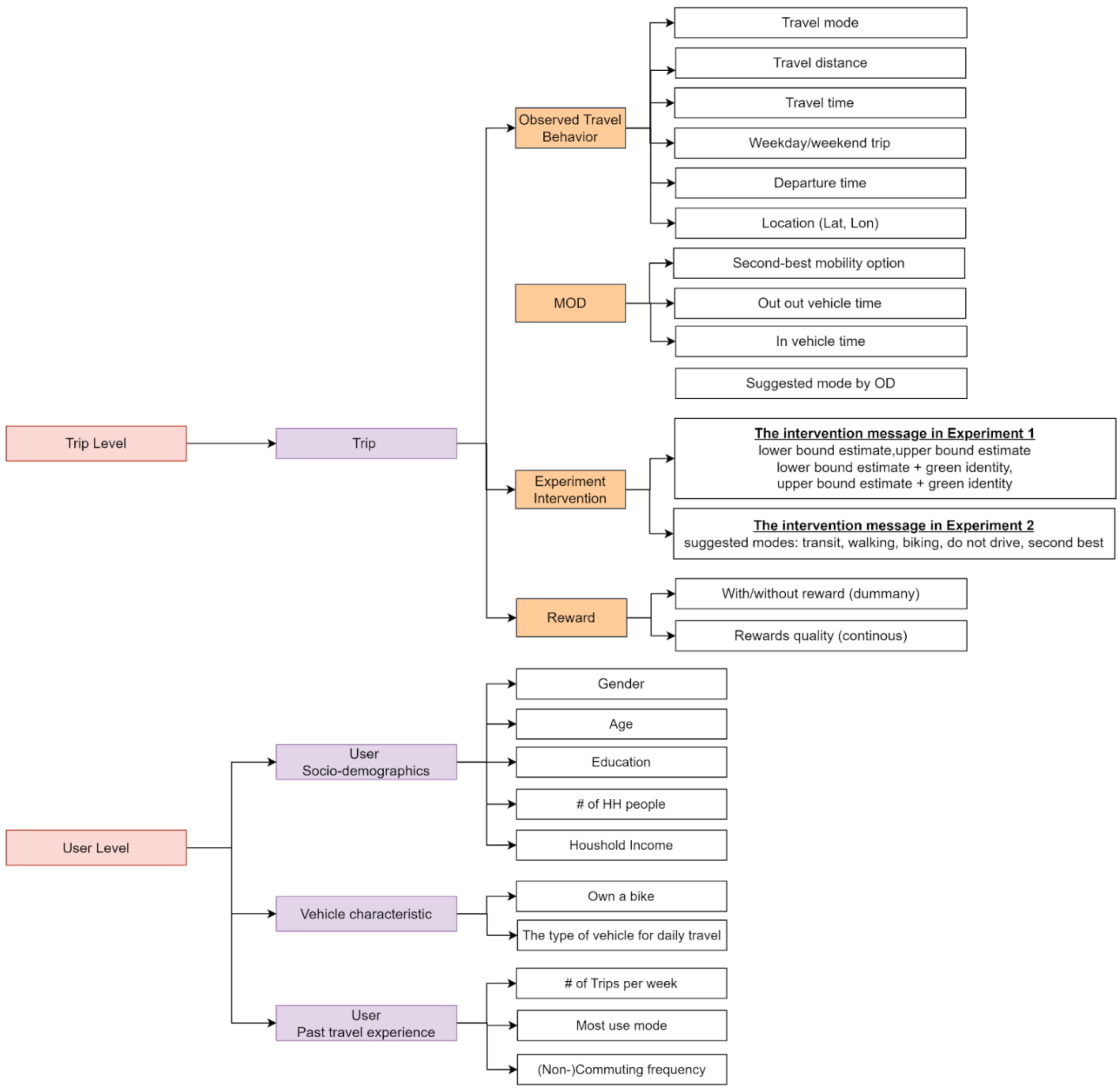

Figure 3-1: Trip-Level and User-Level Variables

The analysis for Experiment 1 was conducted using a total of 33,386 planned non-habitual driving trips, undertaken by 157 users. The OLS and LPM analysis for Experiment 2 is based on 69,384 predicted upcoming habitual driving trips, while the MLR model specifically focused on analyzing the treatment effect of completed driving 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.

3.2 Data Analysis

This section provides an analysis of the user demographic characteristics, transportation options and vehicle ownership, trip type and frequency, trip accessibility characteristics, and transit accessibility and usage, as well as participants' inclinations towards green travel. By examining these aspects in detail, preliminary insights into the participants' behaviors and preferences were gained to better correlate the experiment's results presented below. Figure 3-2 illustrates the participant’s residence locations while the following section provides an analysis of the socio-demographic characteristics such as gender, age, income to provide a deeper understanding of their profiles.

3.2.1 Demographic Characteristics

Based on the information provided by the survey respondents, the gender distributions were compared to the Bay Area population distribution as identified in the MTC Open Data Catalog (Metropolitan Transportation Commission 2019a; 2019b). On the aggregate, the participants’ gender percentages were similar to the Bay Area population with the survey female and male respondents representing 59.3 percent and 39.8 percent respectively compared to the Bay Area female and male population of 50.6 percent and 49.3 percent. The study included a diverse age group of participants from 24 to 75 years old. The average age was 45.4 with a majority of participants (43.8%) falling in the range of 35-44 years old. This is older compared to the median age in San Francisco of 38.3 years (U.S. Census Bureau 2022).

Cao et al. (2009) demonstrated that geographic context, particularly the urban vs. rural setting, exerts a significant influence on travel behavior. The availability of, and proximity to, public transportation and other local amenities can dramatically shape travel behavior. In addition, household income significantly influences travel choices, as indicated by Srinivasan and Ferreira (2002). Higher-income households tend to own more vehicles and often opt for private vehicle use over public transportation, leading to divergent travel behaviors. Paez and Whalen's research (2010) underscores that higher educational attainment often correlates with an increased awareness and adoption of sustainable travel behaviors.

Therefore, in addition to gender and age, the participants, place of residence, household income, and education level were analyzed. Figure 3-3 illustrates that the majority of the participants lived in the counties of San Francisco (28.2%), Alameda (23.6%) and Santa Clara (18.1%). The participants' household income ranged from $25,000 to over $150,000, with 26.3% in the high-income group and 16% in the low-income group. Finally, the majority of participants graduated from college with a four-year degree (46.8%) and 24.1% with a master’s degree or PhD.

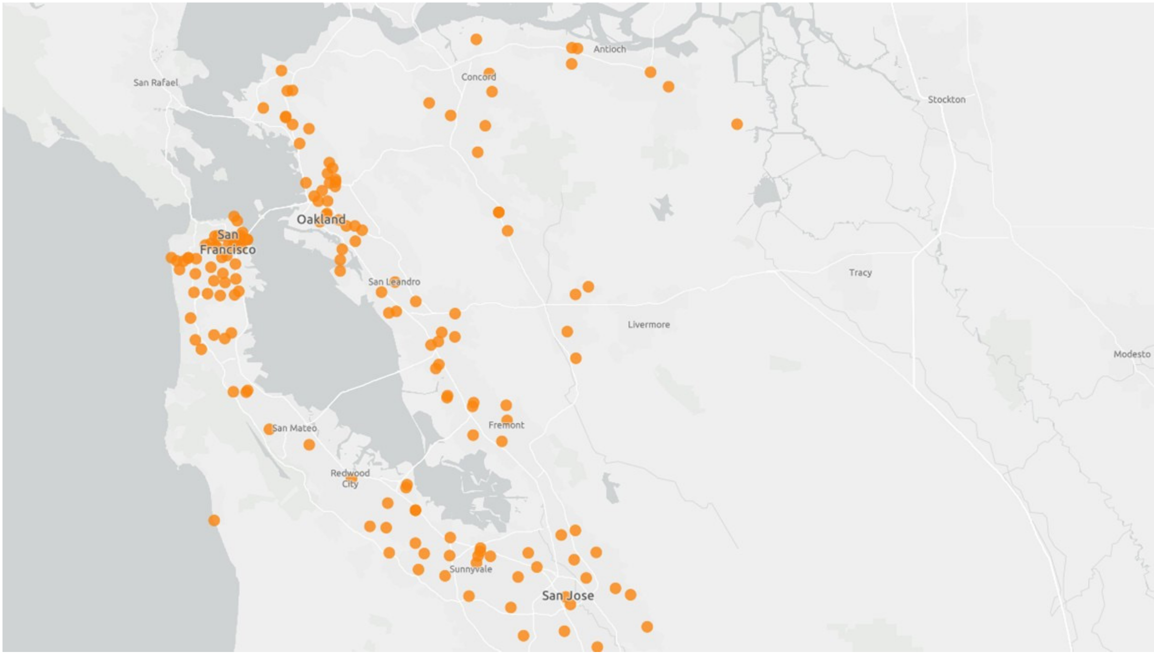

Figure 3-2: Participant Residence Location Distribution

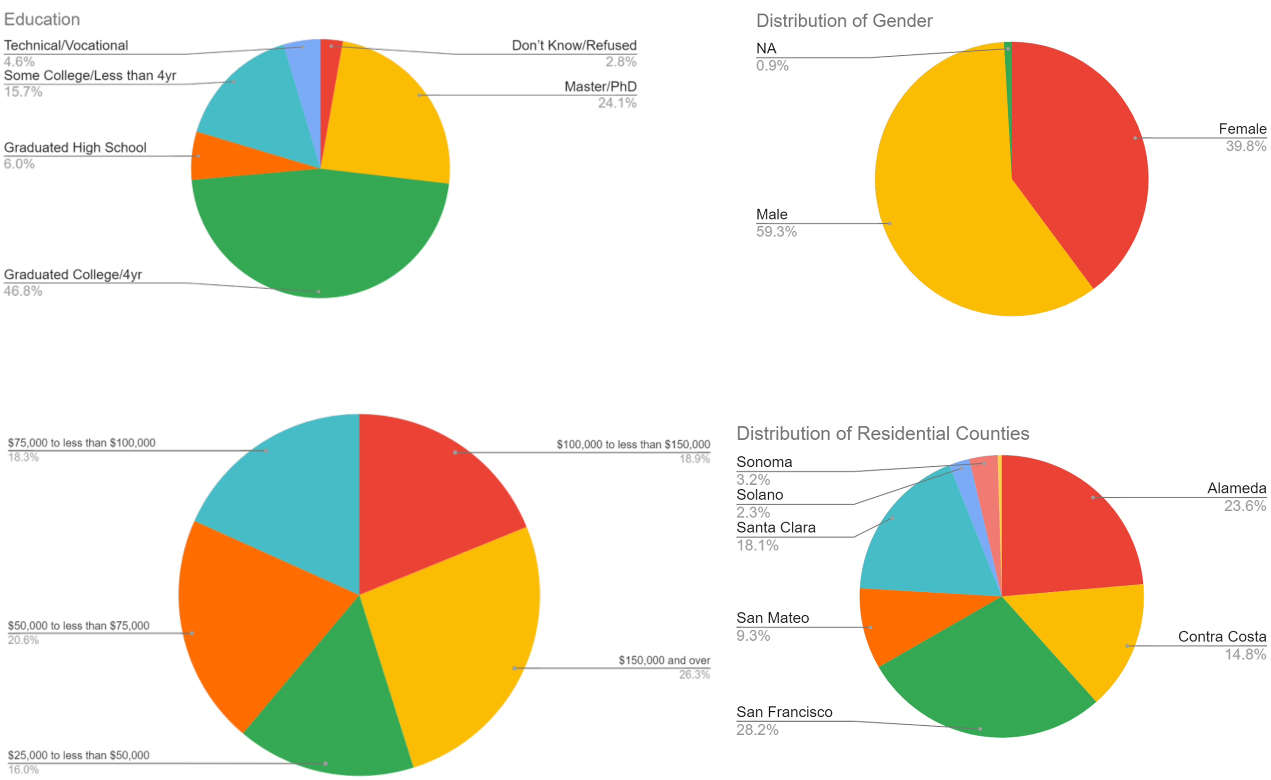

Figure 3-3: Demographic Characteristics of Participants in Survey

3.2.2 Transportation and Vehicle Ownership

In addition to the socio-demographics, an analysis of the transportation preferences of the participants was undertaken revealing that driving was the predominant mode, as Figure 3-4(a) illustrates. In addition, an 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. As Figure 3-4(b) illustrates, 19.9% of the participants owned electric, fuel cell or hybrid vehicles. Finally, participants were asked about bicycle availability, with 45.8% responding positively as shown in Figure 3-4(c).

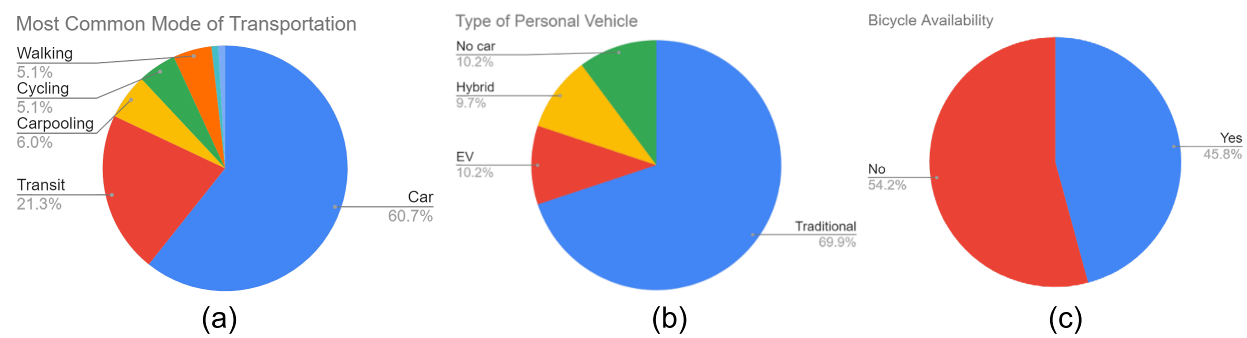

Figure 3-4: Transportation Habits, and Bicycle Availability

3.2.3 Trip Type and Frequency

The data in Figure 3-5(a) shows that 50% of respondents reported commuting 4 to 6 days per week, while 28% reported commuting 1 to 3 days per week. 7.9% reported commuting 0 days per week, and 14% reported commuting 7 or more days per week. This indicates that a significant portion of the sample has a high frequency of commuting, with the majority commuting 4 to 6 days per week. On average, more than 70% of users have a combined total of more than six trips, for both commuting and other journeys, as shown in Figure 3-5(b).

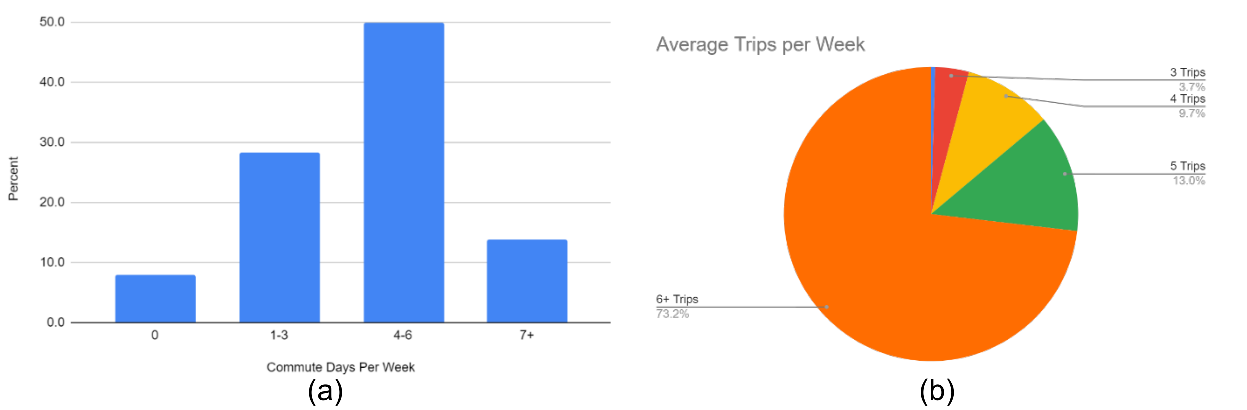

Figure 3-5: Weekly Commute and Trips

3.2.4 Trip Accessibility Characteristics

Figure 3-6 and Figure 3-7 illustrate the distribution of trip distances and travel times for the 7,443 completed habitual driving trips recorded by GoEzy. The average trip distance was 5.8 miles, while the average travel time was 27.7 minutes.

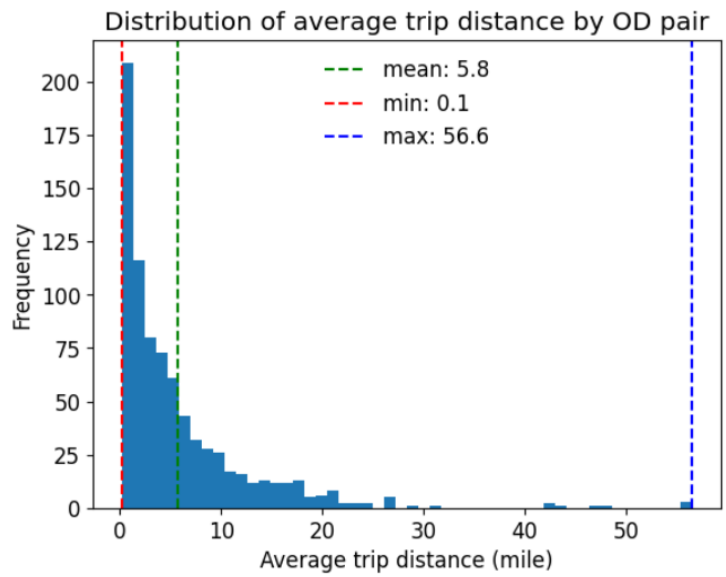

Figure 3-6: Trip Distance Distribution

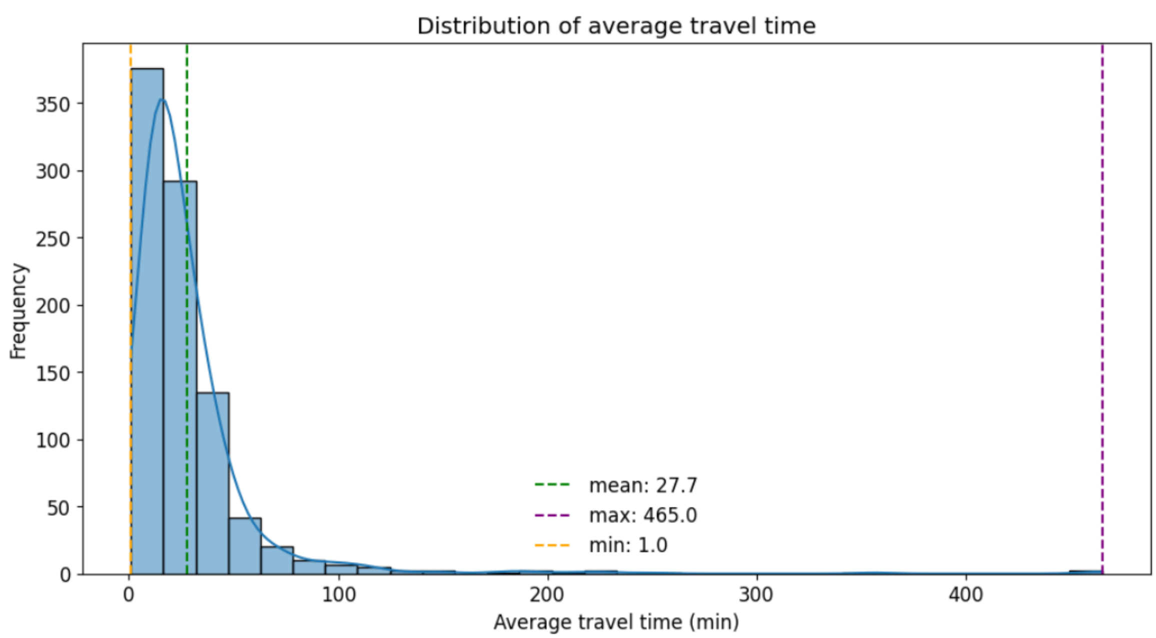

Figure 3-7: Travel Time Distribution

3.2.5 Transportation Patterns

Transportation patterns of the participants were examined using visualizations of the concentrations of all origins and destinations in the area. Figure 3-8 illustrates that the top 100 origin-destination (OD) pairs indicate that a substantial majority of trips are concentrated in Contra Costa, San Mateo, and Alameda 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.

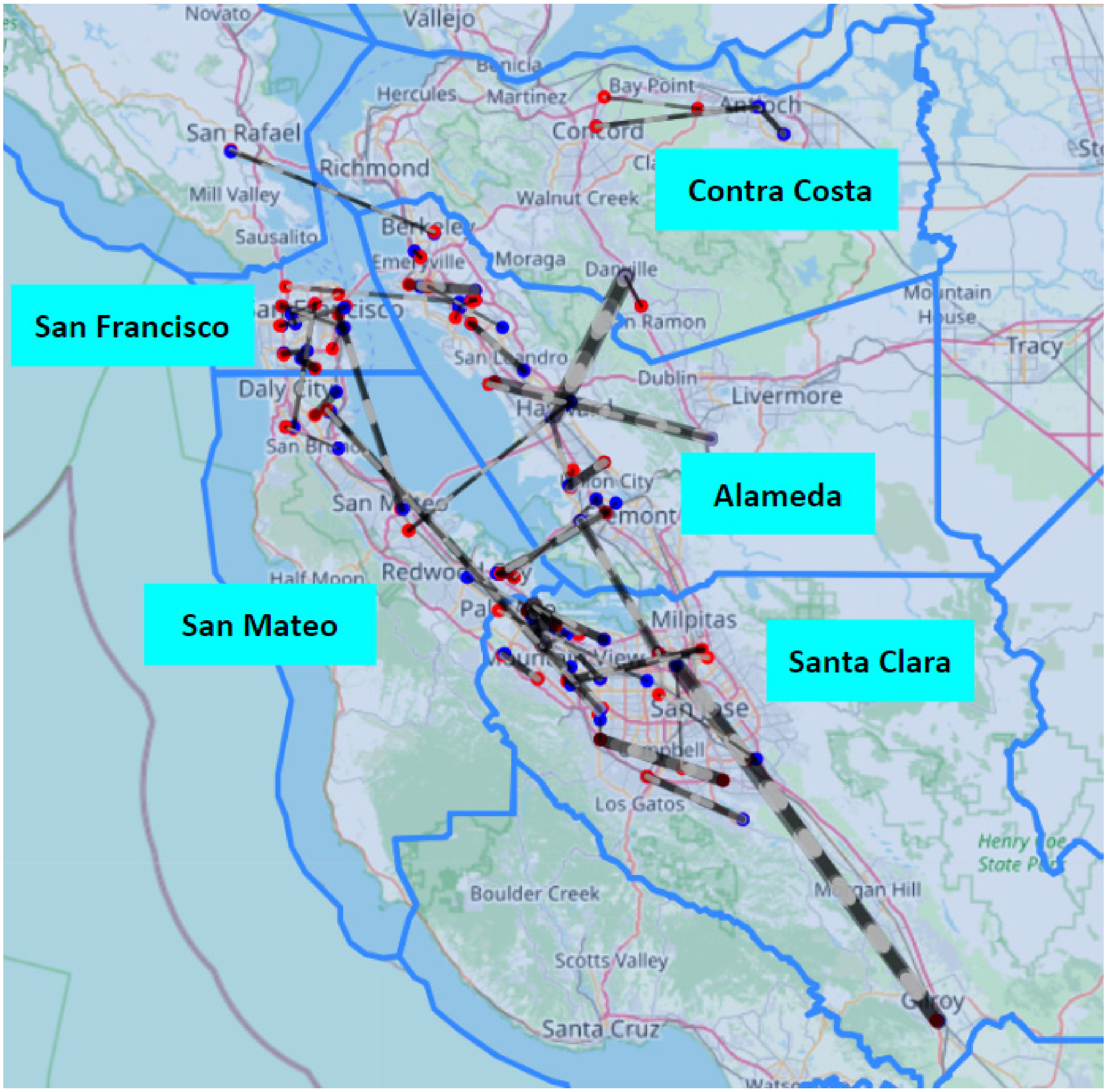

Figure 3-8: Top Habitual OD Pairs During Pilot

3.2.6 Transit Accessibility and Usage

To better understand the appeal of transit for predicted upcoming habitual trips, the MOD module, described in Section 2.3, was utilized and the results indicated that for the ODs where the transit option has an attractiveness of less than 5%, the total transit travel time (including access, transfer, and in-vehicle times) is approximately 80 minutes, as illustrated in Figure 3-9, due to the excessive average walk to transit time of 55.3 minutes. Conversely, the remaining 40% of ODs have reasonable walk times ranging from 2.5 to 16 minutes. Notably, for OD trips where the transit attractiveness is between 10% and 15%, the average transit travel time is around 32 minutes and higher transit attractiveness could be achieved when the transit travel time is halved.

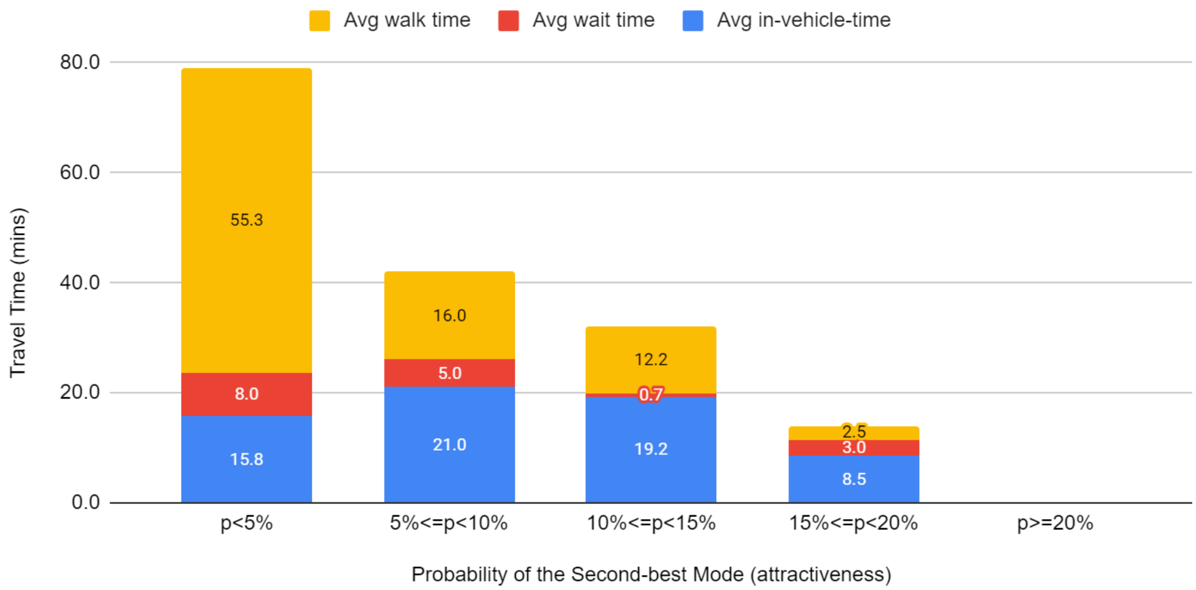

Figure 3-9: Transit Option Attractiveness

Figure 3-10 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 completed 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.

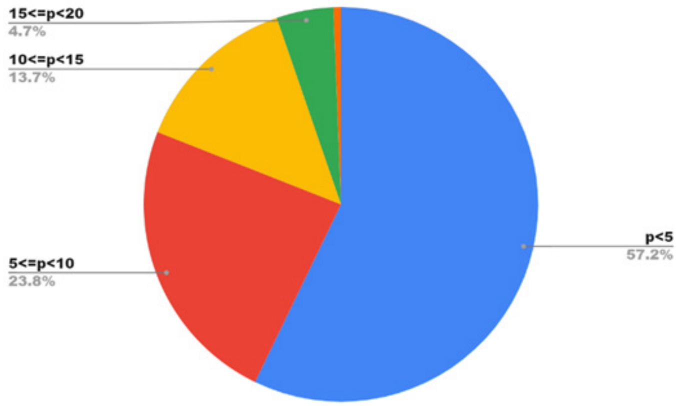

Figure 3-10: All OD Pairs Percentage in Transit Feasibility

4 EXPERIMENT 1 - DESIGN, ANALYSIS AND FINDINGS

Experiment 1 focused on planned non-habitual driving trips, which generally involve one-off decision-making processes for travelers. The OLS and LPM regression models were used to assess the effectiveness of informational nudges[5] (i.e., messages) that leverage behavioral principles, specifically loss aversion, to promote the adoption of active and shared travel modes. The nudges highlight the potential losses associated with continued reliance on driving and emphasize 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 aim to motivate travelers to consider mode shifts towards more sustainable transportation options. To that extent, trip cost related messages and green identity messages (i.e., messages that reminded individuals of their pre-stated intentions to change their behavior for the good of the environment) were used as treatments and their impact on travel mode choice was analyzed.

4.1 Design

Non-habitual driving trips were randomly separated into two categories: treatment and control. 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, as illustrated in Figure 4-1.

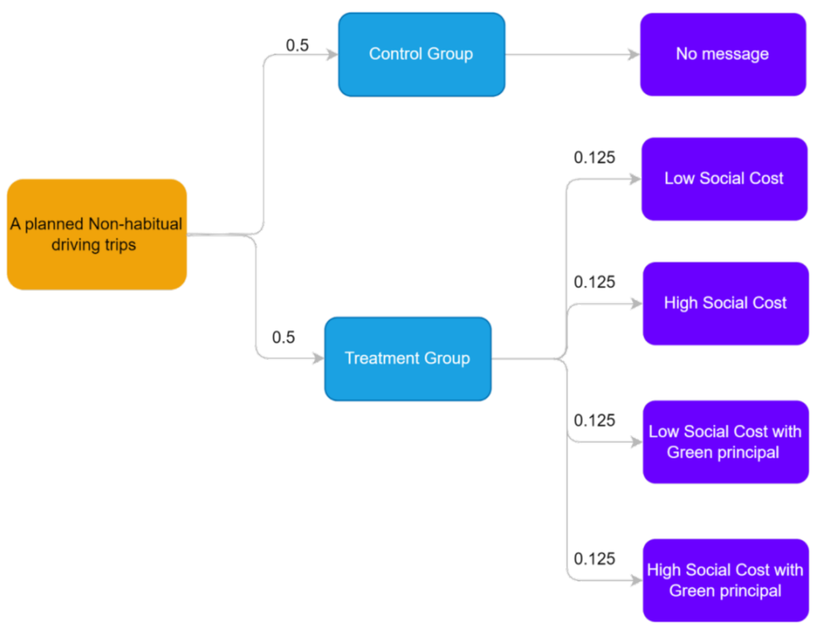

Figure 4-1: Experiment 1 Control and Treatment Groups

[5] 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 groups of individuals.

Five different interventions were administered, summarized in Table 4-1, pertaining to the trip cost and user's pre-stated intentions to change their behavior to help the environment (i.e., "green identity message"), The lower bound (L) of the driving costs was fixed at $1 and the upper bound (H) was fixed at $3 taking into account various factors including trip distance, estimated carbon emissions, relevant congestion, and tolls. Figure 4-2 illustrates the process of users receiving information tiles on their mobile devices, along with a visual representation of the message content.

Table 4-1: 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 principal	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 principal	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 4-2: Suggested Information Tiles Journey for Experiment 1

4.2 OLS Regression and LPM Models Analysis

The analysis included a total of 33,386 planned driving trips[6]. The outcome variables (Y) reflect; 1) trip completion regardless of which mode was used after the intervention (binary, Y=1) ; 2) trip completion via car after the intervention (binary, Y=1); 3) trip completion by walking after the intervention (binary, Y=1); 4) trip completion by cycling after the intervention (binary, Y=1); 5) trip completed via public transit after the intervention (binary, Y=1); 6) the total number of car-based trips made in the twenty-four hours following the intervention (continuous); and 7) the total number of non-car-based trips made in the twenty-four hours following the intervention (continuous).

4.2.1 Effect of Trip Cost Message

The analysis (Appendix B, Table B-1) indicates that the upper bound trip cost message intervention led to a substantial decrease of 86 percentage points[7] in the likelihood of participants completing trips by car within the twenty-four hours following the intervention, which was statistically significant at the 10% level. However, when participants were presented with the 'lower bound trip cost' information—which incorporates both the 'lower bound' and 'cost' details—there was a small but statistically significant increase in participants switching to cycling trips (Appendix B, Table B-2).

These findings are quite intriguing. The significant 85% 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 study and replication is necessary in future research endeavors.

4.2.2 Effect of Green Identity Treatment

When we collapsed across treatment conditions (i.e., looking at the effect of receiving a cost estimate message or looking at the effect of receiving the green identity message), 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 B, Table B-3).

Receiving treatment resulted in a small but statistically significant increase of 0.08 percentage points in completed cycling trips (in other words, individuals who received a treatment condition were slightly more likely to complete their trip by bike) 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 B, Table B-4).

In conclusion, the study suggests that receiving a treatment intervention, when presented during trip planning, led to a slight but significant increase in the likelihood of trips being completed by cycling and

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[6] The estimation results in sections 4.2.1-4.2.3 may have different total sample sizes due to variations in the selection criteria of the sample (X) when estimating the effects.

[7] Percentage point refers to a unit of one percent. For example, the difference between 20% and 25% is an increase of 5 percentage points.

an increase in the number of trips completed using non-car modes in the 24-hour period after the intervention.

4.2.3 Interaction Effects

The initial simple LPM 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. Moreover, they showed a substantial decrease in traveling by car in the twenty-four hours following the intervention, with a decrease of 183 percentage points[8] (Appendix B, Table B-5). These “flexible traveler” participants were significantly more likely to choose non-driving modes in the twenty-four hours after the intervention, with an increase of 37.4 percentage points (Appendix B, Table B-5).

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.

[8] Percentage point refers to a unit of one percent. For example, the difference between 20% and 25% is an increase of 5 percentage points.

5 EXPERIMENT 2 - DESIGN, ANALYSIS AND FINDINGS

Experiment 2 focused on predicted habitual driving trips[9] and utilized the OLS and LPM models to examine the effects of a composite treatment[10] 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 MLR 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 received messages and incentives. 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 habitual driving trips were recorded and analyzed by the OLS and LPM models, with 34,582 trips associated with the control group and 34,802 trips associated with the treatment group. In addition, the MLR model focused on analyzing the treatment effect on 7,433 completed habitual driving trips.

5.1 Design

Predicted upcoming habitual driving trips were divided into the control group and five (5) treatment groups, as illustrated in Figure 5-1. The control group is comprised of 50% of the predicted habitual driving trips and the remaining 50% is equally allocated to each treatment group which received messaging pertaining to public transit, walking, cycling, not driving, and choosing the second-best mode).

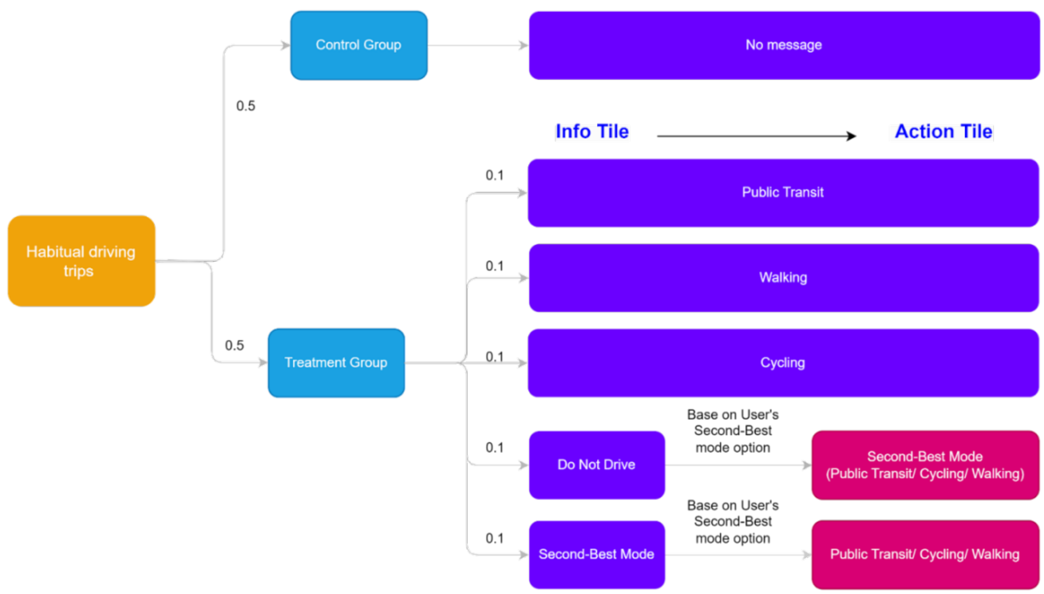

Figure 5-1: Experiment 2 Control and Treatment Groups

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

[10] 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.

For each day of the experiment, users whose predicted habitual driving trips were assigned to the control group did not receive an intervention, while users whose predicted habitual driving trips received suggestions to switch to Public Transit, Walking, or Cycling. Users whose predicted 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 the Do Not Drive treatment group did not voluntarily change their mode, an Action tile was sent suggesting the most suitable and appealing second-best mode of transportation for their specific trip, based on the MOD module calculation.

Table 5-1 summarizes the interventions administered to the various treatment groups. The amount offered in the treatments follows an Erlang distribution[11], illustrated in Figure 5-2 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, the incentive offers must be randomized to account for the switch behavior under various conditions. This ensures that responses from various conditions in relation to the offered incentive are captured.
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 in for gift cards from GoEzy's marketplace.

Figure 5-3 illustrates the process of users receiving information tiles and action tiles on their mobile devices, along with a visual representation of the message content.

[11] The Erlang distribution, a continuous probability distribution, is often used in experimental design to model the time between independent events that occur at a constant rate. It provides insights into the frequency and amount of incentives proposed to participants to nudge their transportation choices. For instance, areas with higher peaks in the distribution indicate incentive amounts that were more commonly offered. These incentive levels can range from $(L) to $(H), as mentioned in the interventions. The Erlang distribution was used to model and understand how often certain incentive amounts were presented and how they might influence the decision-making of participants. Observing where the distribution peaks or troughs can help in optimizing incentive-based interventions in future research.

Table 5-1: Experiment 2 Interventions

Category	Group	Intervention	Tile (60 minutes before trip)
Control	Control	None	None
Treatment	Random Mode	Public transit nudge with incentive	Info Tile (push notification) 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 (push notification) 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 (push notification) 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?
Treatment	Base on user's Second-best Option in action tile	Do not drive nudge with incentive	Info Tile (push notification): 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 (push notification) 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?

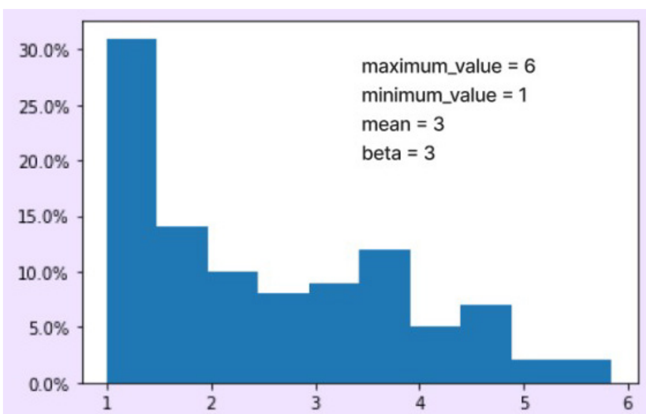

Figure 5-2: Reward Distribution

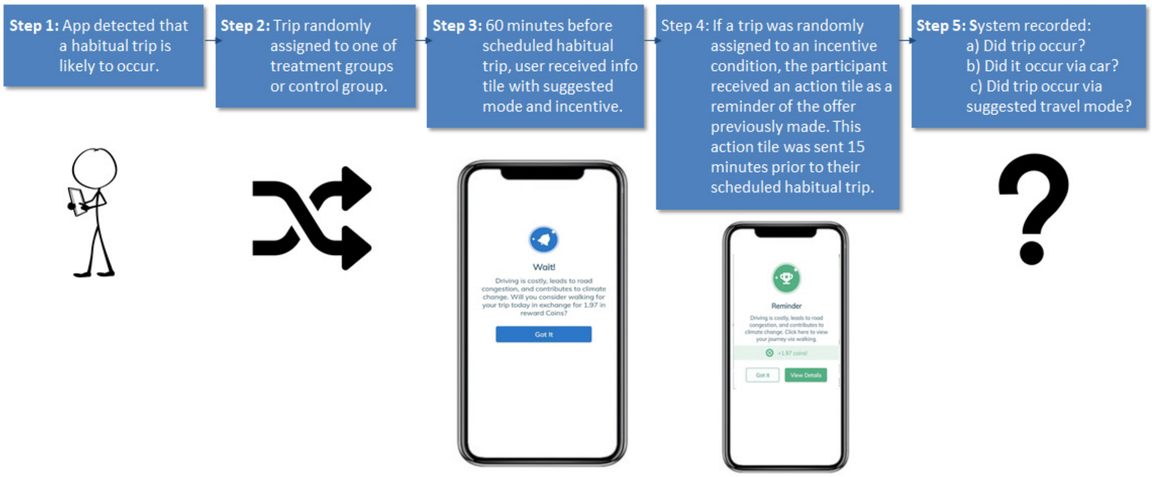

Figure 5-3: Suggested Information and Action Tiles Journey for Experiment 2

5.2 OLS Regression and LPM Models Analysis

The OLS and LPM models were utilized to assess the impact of message-based interventions and monetary incentives on travel mode choice. The message interventions suggested non-car travel modes to recipients, while the incentive interventions offered a monetary reward ranging from $0 to $6.

The analysis was conducted using data collected from 84 participants, for whom the system predicted a total of 69,384[12] upcoming habitual driving trips. The dataset consisted of a control group (n=34,582) that did not receive any intervention and a treatment group (n=34,802) that received the intervention.

The outcomes examined were as follows:

- Completion of the predicted upcoming habitual driving trip.
- Completion of the predicted upcoming habitual driving trip via car.
- Completion of the predicted upcoming habitual driving trip via any non-car mode.
- Completion of the predicted upcoming habitual driving trip via public transit.
- Completion of the predicted upcoming habitual driving trip via walking.
- Completion of the predicted upcoming habitual driving trip via cycling.
- Completion of the predicted upcoming habitual driving trip via multiple modes (i.e., intermodal).

5.2.1 *Effect of Composite Treatment*

The analysis of the composite treatment's (see footnote 10) impact revealed that, overall, it did not yield significant effects, except for a small but statistically significant increase in the likelihood of users completing their predicted upcoming habitual driving trips by non-car modes, with an increase of 0.2 percentage points at the 10% level. However, the results did not show a clear preference for any specific travel mode, such as walking, cycling, or public transit (Appendix C, Table C-1).

[12] It's essential to note that these are system-generated predictions and not the actual number of trips undertaken. The primary purpose was to consistently capture potential daily driving habits, which resulted in the noted trip predictions.

5.2.2 Effect of Receiving a Mode Specific Nudge

After assessing the effect of message interventions on travel mode choice, the analysis revealed some interesting findings. Participants who received the "Do not drive" message were slightly more likely to complete their trips via non-car modes, with a 0.38 percentage points increase, which was statistically significant at the 10% level. Additionally, they were also slightly more likely to cycle, with a 0.16 percentage points increase, significant at the 10% level. These findings indicated a 17% increase in non-car mode usage and a 65% increase in cycling relative to the control group. Comparing with the control group is crucial to understanding the relative significance of these increases due to the treatment's application. This comparison helps isolate the true impact of the treatment on observed behavior change, considering that both groups may be subject to similar endogenous factors, and the only difference lies in the treatment received.

On the other hand, participants who received the "second-best mode option" message took 6% fewer completed trips via car than the control group. These same participants saw an increase in their use of non-car modes by 20% relative to the control group. Notably, within this uptick, trips completed by walking increased by 0.4 percentage points — a 22% increase when compared to the control group. This increase was statistically significant at the 5% level (Appendix C, Table C-2).

These experiments highlighted the effectiveness of messaging in shifting habitual trip travel behavior. However, these messages need to be carefully crafted with feasible mode options and incentives, as shown in this experiment. Messaging-based interventions were shown to be cost-effective and relatively straightforward to implement. Notably, the most effective messages were those offering specific mode recommendations tailored to the given trip, such as "do not drive" or the "second best option." In contrast, mode-specific messages, like "cycle," "walk," or "use public transit," did not substantially shift travel behavior as the modes recommended were not personalized to the participant and were likely not an attractive or feasible option. Overall, these findings provide valuable insights into leveraging personalized messaging to encourage non-car travel options and promote sustainable travel behaviors.

5.2.3 Effect of Any Mode Nudge When Car is the only Appealing Mode

The objective of this analysis was to investigate the impact of nudges when driving was the only mode with a probability greater than 10%, as determined by the MOD process discussed earlier. When the trips were segmented based on the feasibility or attractiveness of sustainable travel mode options (defined as having a probability of 10% or greater), the results indicated that the nudges did not have any effect when driving was the only attractive travel option (Appendix C, Table C-3).

Additionally, the treatment effects were consistent across various trip characteristics and treatment groups. This consistency implies that the impact of the nudges remained relatively constant regardless of the specific trip details or different groups of participants.

This analysis concludes that the nudges become more influential when they include feasible and attractive choices available to the participants. Understanding these nuances can help tailor and optimize message-based interventions to promote sustainable travel choices effectively.

5.2.4 Effect of Incentives

The analysis of incentives in isolation from other interventions did not demonstrate a significant effect in general (Appendix C, Table C-4). However, the introduction of varying amounts of incentives notably influenced travel mode selection, specifically for intermodal transportation options.

When an incentive of $3 was offered, there was a significant increase of 2.4 percentage points in the likelihood of users completing their predicted upcoming habitual trips using intermodal transportation options (i.e., incorporating transit and walking when using other modes like cars or bike) for their trips. This effect became more pronounced with a higher incentive value of $5, resulting in a significant increase of 9.8 percentage points in the likelihood of users completing their predicted upcoming habitual trips using intermodal (Appendix C, Table C-5).

These findings indicate that the effect of incentives for intermodal transportation options have an inflection point at $3 or greater. In other words, lower incentives were not sufficient to trigger any interest or behavior change from the participants, but once the incentive reached $3 or higher, it started to have a significant impact on encouraging intermodal travel choices.

Understanding the thresholds and levels at which incentives become effective can help in designing more targeted and impactful incentive-based interventions for promoting sustainable and intermodal transportation options.

5.2.5 Effect of Interaction Terms

Interaction of 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 sustainable modes of transportation.

On the other hand, among users between the ages of 57 to 76, Among individuals aged 57 to 76, there was a slight decrease in their preference for cycling. However, when these individuals were introduced to measures promoting sustainable transport, their inclination towards cycling showed a marginal rise[13]. (Appendix C, Table C-6).

These results demonstrate the potential for targeted interventions based on age groups. The treatment appears to be more effective in encouraging behavior change among users aged 37 to 56, leading to reduced driving and increased use of public transit and cycling. For users aged 57 to 76, even though there was initially a small dip in their cycling habits, the introduction of sustainable transport measures led to a favorable shift towards cycling. This insight highlights the importance of tailoring interventions to specific age groups to maximize their effectiveness in promoting sustainable travel choices.

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[13] Specifically, there was a 0.05% decrease initially, but with the sustainable transport measures, there was a 0.04% increase in their choice of cycling.

Interaction of Treatment and Mode Flexibility

As in Experiment 1, a subset of participants was flagged as "flexible" users 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 C, Table C-7).

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 treatment may have had a less pronounced effect on these specific travel modes for this group. 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 non-driving modes and walking among flexible users.

5.3 MLR Model Analysis

The MLR model utilizes two variable categories referred to as "Lower-Level Variables" and "Upper-Level Variables", organized into two distinct levels, as depicted in Figure 5-4.

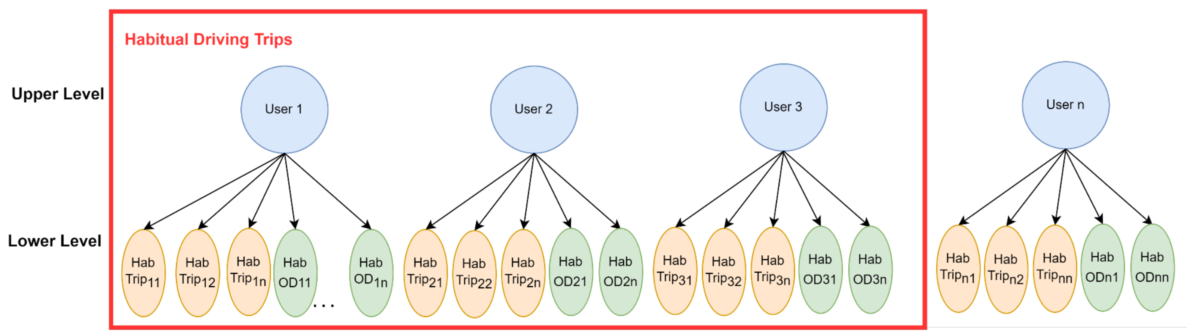

Figure 5-4: Experiment 2: Trip-Level and User-Level Characteristics

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 D-1in Appendix D 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 habitual driving trips completed by these users. For the purposes of the MLR analysis, the individual completed habitual driving trip was associated with their important location clusters (see Section 2.1.1) 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 MLR model was estimated using the maximum likelihood method with the dependent variable indicating whether the habitual OD pair had changed to a non-driving mode after users received the suggested mode tile:

- “1” was assigned to a completed habitual driving trip if the user changed to a non-driving mode after receiving the treatment.
- “0” if the user did not change from driving.

The analysis aimed to identify the factors that influenced the likelihood of mode change for the OD pair.

The MLR demonstrated a superior fit to the data, as supported by the residual intra-class correlation coefficient (ICC) (see Section 2.5.2), a key statistic used to evaluate the performance of multilevel models (Hilbe, 2009). The ICC value was 0.763[14] 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. Table D-2 in Appendix D summarizes the MLR model explanatory variable coefficients as well as, the associated p-values and Odds Ratio.[15]

5.3.1 Effect of Message Type on Travel Mode

The MLR results indicated that receiving a walking tile during peak hours increased the likelihood of using non-driving modes for the habitual OD of the trip (almost 14 times higher when a recommendation was received). Conversely, receiving a cycling tile during peak hours did not have a similar effect. It is possible that the lack of a significant effect for receiving a cycling tile during peak hours is because some users may not have owned or had access to a bicycle. However, public transit messages did not demonstrate a significant effect in the model.

5.3.2 Effect of Incentive on Travel Mode

The random distribution of walking and cycling tiles with rewards increased the likelihood of trips associated with a habitual origin-destination (OD) pair being undertaken with non-driving modes.

The provision of a reward for users for whom transit is an attractive option (i.e., MOD module), increased the likelihood (coefficient = 0.658) of switching to non-driving modes for the habitual OD of the trip. The Odds Ratio of 1.93 indicates that for each additional unit of the MOD module with rewards, the odds of switching to non-driving modes for the habitual OD of the trip are 1.93 times higher compared to not switching. In other words, the presence of the MOD module and incentive substantially increases the likelihood of choosing non-driving modes for the trip.

Offering rewards for using transit when the access time was less than 15 minutes proved effective in promoting public transportation use. The analysis indicated that such a treatment increased the likelihood of switching to non-driving modes for the habitual OD of the trip. The 3.38 value of the Odds Ratio suggests that the likelihood of using transit is three times higher than driving. This finding suggests that offering monetary incentives can effectively encourage the use of non-driving modes for the habitual OD of the trip when out-of-vehicle travel time (OVTT) of public transit is manageable.

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

[15] 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.

5.3.3 Effect of Incentive with respect to the Second-Best Mode Option

The rewards disbursed for two treatment types, one presenting the user with the second-best mode (based on the MOD calculations) option and the other presenting the user with a random mode option, were further analyzed. The analysis found the average reward for the second-best mode treatment was $1.90, whereas for the random mode treatment it was $2.04. Furthermore, the maximum reward was $2.66 for the second-best mode and $3.04 for random modes. The analysis suggests that the average and maximum reward values tend to be lower when the user is presented with an appealing non-driving mode. Figure 5-5 illustrates the distribution of rewards for the two treatments.

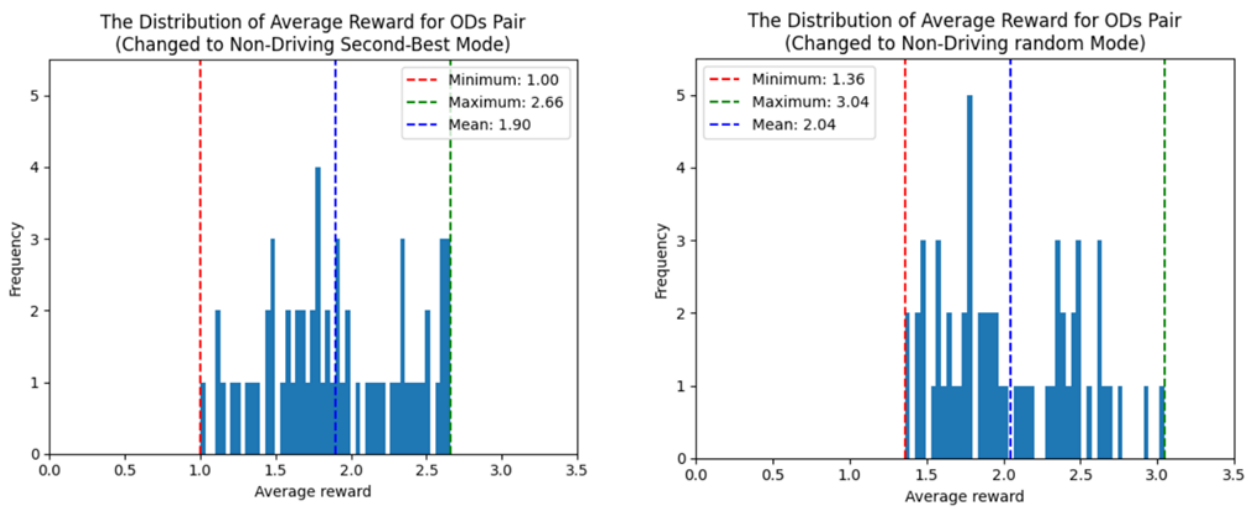

Figure 5-5: Distribution of Rewards with the 2nd-Best Mode Options vs Random Options

5.3.4 Effect of Trip Characteristics

An analysis was undertaken to examine the effect of distance and travel time, illustrated in Figure 5-6 and Figure 5-7, on behavior change. Results indicated that users who changed to the non-driving mode presented had a considerably lower average travel time (22.9 vs. 26.6 minutes) and trip distance (3.7 vs. 6.1 miles), as compared to users who did not change to the non-driving mode presented. This result suggests that behavior interventions may be more effective for shorter trips.

For users receiving walking tiles, the associated travel distance was less than 3 miles and the likelihood of trips being undertaken by non-driving modes significantly increased (coefficient value of 0.383, odds ratio of 1.47). This observation aligns with the findings by Saelens and Handy (2008), who reported that individuals demonstrated a preference for active transportation modes for shorter trips.

In addition, the receipt of cycling tiles for a travel distance ranging between 3-10 miles significantly increased the likelihood of trips being undertaken with by bicycle. This is corroborated by research conducted by de Nazelle et al. (2011), who found that individuals residing within a 10-kilometer (i.e., about 6.25 miles) radius from their workplace exhibited a higher propensity to choose cycling as their primary mode of transportation.

Furthermore, an average OD pair travel time of less than 5 minutes by car exerted a significant positive effect on trips converting to non-driving modes (coefficient value of 4.095). This observation is in line with the study by Bohte and Maat (2009), who identified travel time as a critical determinant in the selection of sustainable transportation modes.

Finally, weekday trips (Monday to Friday) exerted a significant positive effect on completed habitual driving OD pairs being undertaken by non-driving modes (coefficient value of 0.357, odds ratio of 1.43). This finding is also substantiated by a study conducted by Mokhtarian and Salomon (2001), who observed that weekday travel behavior was more receptive to modifications in transportation policies compared to weekends.

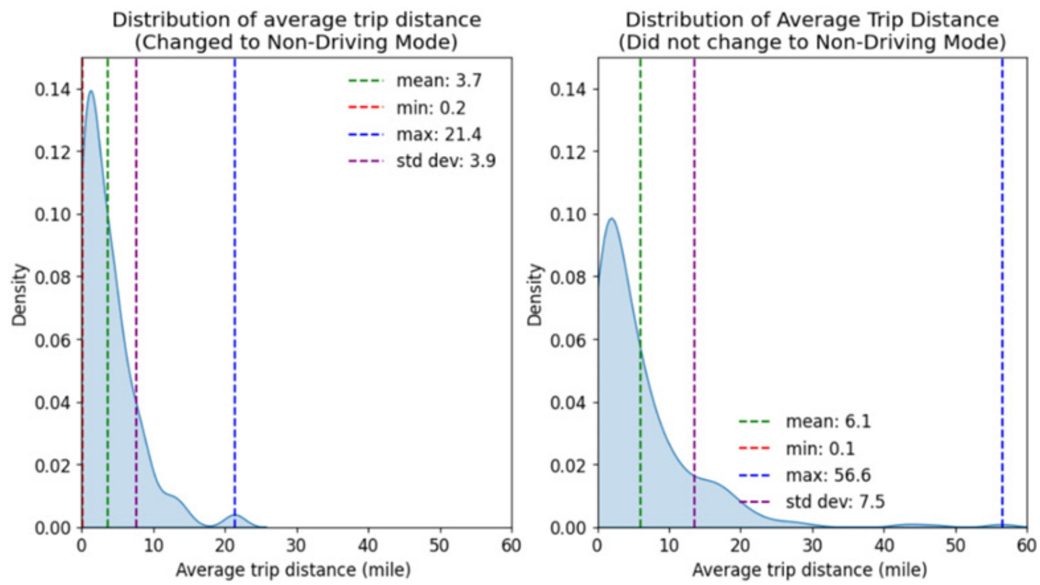

Figure 5-6: Comparison of Trip Distance Distribution by ODs Pairs

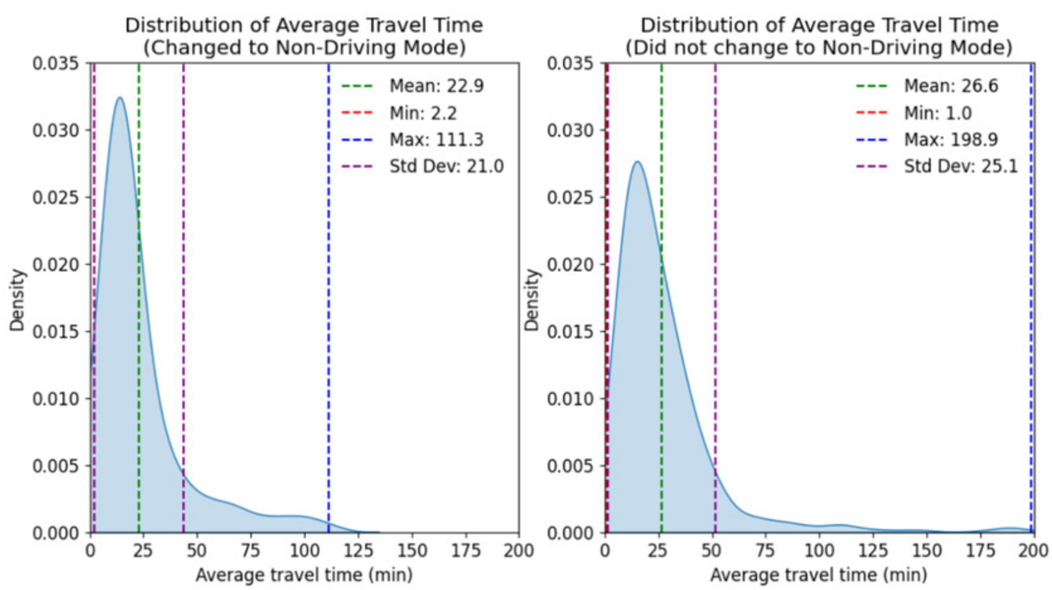

Figure 5-7: Distribution of Average Travel Time by ODs Pair

5.3.5 User Attributes

As Table D-2 in Appendix D indicates, the bicycle availability variable strongly influenced the likelihood of trips between habitual driving origin-destination (OD) pairs being undertaken by non-driving modes. It was associated with a high coefficient value of 6.17 and an exceptional odds ratio of 480.62. This odds ratio value suggests that for each unit increase in bicycle availability, the odds of the outcome occurring increase 480.62 times compared to when bicycle availability does not increase. This means that the availability of cycling options plays a significantly influential role in encouraging non-driving transportation modes for habitual driving OD pairs. This conclusion is supported also by research, such as the study conducted by Fitch et al. (2022), which found that implementing a bicycle lending program can increase bicycle commuting by 1.7-2.3 days per week, leading to substantial behavior change. Additionally, Fitch (2019) indicated that electric bicycles have been shown to significantly increase cycling while decreasing driving. Moser et al. (2018) found that participants who purchased e-cycles showed a decrease in car habit association and an increase in e-cycle habit association, suggesting that regular use of e-cycles can help establish a new habit of using sustainable transportation.

Table D-2 indicates that "bicycle ownership" has 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.

Moreover, Table D-2 shows that residents of Contra Costa, San Francisco, and Santa Clara counties are more likely to opt for non-driving modes of transportation. In Contra Costa, this was particularly observed in cities like Danville (94526) and Antioch (94509). In Santa Clara, cities such as Palo Alto (94303), Los Altos (94024 and 94022), San Jose (95123 and 95132), and Campbell (95008) exhibited this trend. It's worth noting that while Contra Costa and Santa Clara are extensive counties known for car-oriented transportation, specific regions within these counties, as indicated by the mentioned zip codes, display a significant shift towards non-driving preferences. Specifically, the odds ratios of 221.05, 17.01, and 748.90 respectively suggest a greater inclination among these residents to switch to non-driving modes than those not residing in these counties, highlighting the considerable influence of geographical location on transportation choices.

These results provide valuable insights into the factors that influence travel mode choices and can inform targeted interventions and policies aimed at promoting sustainable transportation options in specific areas.

6 SUMMARY OF FINDINGS

The Pilot undertook two behavioral experiments, where various monetary and non-monetary interventions were promoted to engage individuals in behavior change. The first experiment targeted non-habitual driving trips and examined the efficacy of informational nudges to encourage travel behavior change towards a sustainable mode. The second experiment targeted habitual Origin-Destination (OD) pairs that utilized monetary incentives (redeemable for gift cards) in addition to informative nudges to influence participant behavior shift. As travelers were recruited, Metropia's GoEzy mobile app was the main medium for the experiment implementation.

The evaluation indicated that message-only interventions had no significant overall effect on participants' travel mode choices. However, presenting walking or bicycling as the 'second best' option effectively encourages users towards more sustainable travel choices. However, for transit to be considered as a favorable option, the addition of an incentive is crucial. This highlights the inherent appeal of walking and bicycling, while stressing the added push required for transit through rewards. Moreover, segment analysis revealed that participants who were identified as being more 'flexible' in their travel modes (i.e., those who traveled using more than one mode in the first week of the study) were more responsive to the interventions. These participants were significantly less likely to complete trips by car after receiving an intervention and were more likely to use non-car travel modes in the twenty-four hours following the intervention.

The evaluation of the effects of monetary incentive and message interventions on completed habitual driving trips indicated that tailored interventions, offering a second-best option based on an individual's environment and trip details, were more effective than generic mode-specific messages. The analysis of the out-of-vehicle travel time (OVTT) and in-vehicle travel time (IVTT), both specifically for transit, for the second-best mode revealed their significant impact on transportation choices. When incentives are used, and IVTT for transit is kept under 15 minutes, a notable change in habitual mode choices occurs. However, if OVTT for transit exceeds 40 minutes, incentives do not generate a significant effect. The analysis highlighted the significant influence of personalized recommendations on transportation choices. For example, the analysis found users to be 14 times more likely to choose walking during peak hours when receiving a recommendation. The analysis emphasized the importance of second-best choice recommendations, which notably influenced individuals to select public transit as their sustainable option. Additionally, compensation for extra travel time was found to play a role in individuals' decisions to opt for public transit. Furthermore, suggesting walking for trips under 3 miles and cycling for trips between 3 and 10 miles had a significant effect on changing habitual mode choices. The presence of bicycles, privately owned or shared, especially in Contra Costa, San Francisco, and Santa Clara, positively influenced individuals' willingness to travel by bike. 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. These findings highlight the potential for sustainable spatial planning and transportation policies to promote more sustainable travel behaviors.

Appendix A Qualification Survey for Incentivizing Active and Shared Transportation Pilot Program

Qualification Survey for Incentivizing Active and Shared Transportation Pilot Program

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

Appendix B OLS Model Result in Experiment 1

Table B-1: Effect of Each 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

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

Table B-2: 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 B-3: 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 B-4: 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 B-5: 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: *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$.

Appendix C OLS Model Result in Experiment 2

Table C-1: 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 C-2: 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 C-3: 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 C-4: 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 C-5: 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

Table C-5: Effect of Varying Amount of Incentive

	Completed Trip	Completed Trip by Mode				
		Car	Non-car	Walk	Cycle	Intermodal
(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.

Table C-6: 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 C-7: 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.

Appendix D MRL Model Analysis

Table D-1: 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
	Exp(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
	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

Table D-1: Descriptions of Variables

Variables		Description	Mean	Min	Max	Type
Upper-Level Variables						
User characteristics	Cycle_ availability	Variable is set to 1 when a bicycle is available.	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 D-2: Statistics

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
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

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