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Multimodal Trip-Chain Planner For Incentivizing Transit Usage

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Multimodal Trip-Chain Planner For Incentivizing Transit Usage

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Following the principles of the USDOT strategic goal of transformation, using evidence-based decision making to turn research into transformative and equitable solutions that take advantage of emerging technologies.

Led by the New York University Tandon School of Engineering, **C2SMARTER's** geographically diverse consortium includes Rutgers University, University of Washington, the University of Texas at El Paso, CUNY- City Tech, Texas Southern University, and North Carolina A&T.

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Executive Summary

The Multi-Modal Trip-Chain Planner is an innovative solution aimed at enhancing mobility for disadvantaged travelers, particularly those with limited access to reliable transportation. This project, a collaboration between New York University and North Carolina A&T State University under the C2SMARTER center, focuses on addressing the mobility challenges of individuals in both urban and rural areas.

The trip planner optimizes routes by integrating various transportation modes, such as public transit, walking, biking, and ridesharing, into a seamless journey. The planner also incorporates real-time data and user preferences, allowing for personalized travel solutions. Importantly, this tool seeks to promote the use of sustainable transportation methods, reduce congestion, and lower carbon emissions by incentivizing travelers to shift from private vehicle use to more environmentally friendly options.

Additionally, the project uses behavioral modeling to analyze how different pricing strategies, such as offering weekly and monthly transit passes, impact revenue and ridership for microtransit services. The model explores how varying levels of discounts can both maximize revenue and incentivize greater ridership. By understanding user behavior and preferences, the project aims to determine the optimal pricing and incentive structures that encourage the adoption of microtransit while balancing financial sustainability.

A survey was conducted to estimate users' preference for the interface of the trip planner and the factors that change people's behavior towards sustainable transportation modes. Respondents showed strong support for trip chaining—the ability to plan multiple trips at once with a choice of mode for each—with 40% favoring the ability to add multiple destinations and 41% preferring to select different modes for various segments of their trip. Cost and travel time information emerged as the top priorities that users want to see, with 66% prioritizing cost and over 50% showing great preference for time. Urban respondents were more open to sustainable transportation modes compared to rural respondents, who cited poor infrastructure, limited public transit options, and longer travel times as barriers. Only 5% of all respondents regularly used public transit, highlighting the need for improved access and incentives, especially in rural areas.

The study introduced an agent-based, nested behavioral model (AMXL) to forecast and manage microtransit services, demonstrating its ability to optimize ride pass pricing and subsidy policies for increased revenue and ridership. In a case study of Via microtransit in Arlington, TX, reducing weekly and monthly ride pass prices boosted daily revenue by $102 and increased consumer surplus by $363. Event- and place-based subsidies also showed potential to reduce car trips and increase microtransit

usage, but would require substantial financial support. For example, a 100% fare discount at AT&T Stadium could reduce 80 car trips per day, but at an annual subsidy of $32,068. These findings underscore the importance of carefully balancing pricing and subsidy policies to enhance the sustainability and efficiency of microtransit services.

The multi-modal trip-chain planner demonstrates potential for improving mobility, particularly for disadvantaged groups, by catering to their specific needs through accessible and inclusive information, though further testing and real-world implementation will be necessary to fully assess its impact. The planner's ability to incorporate multiple transportation modes and user preferences, combined with behavioral models that predict decision-making, is crucial for promoting the adoption of sustainable transportation. However, significant barriers remain, particularly for rural populations who face infrastructure and connectivity challenges.

To encourage the adoption of sustainable transportation, policymakers should prioritize infrastructure improvements, particularly in rural areas where public transit and alternative travel options like walking and biking paths are limited. Investing in better infrastructure is essential for reducing reliance on private vehicles and making sustainable travel a viable option for more people. Additionally, incentive programs that reward the use of public transit and other eco-friendly modes, such as microtransit or shared rides, should be implemented. These could include credits, discounts, or other rewards that encourage frequent use of sustainable options, helping to reduce congestion and promote environmentally conscious travel choices. Finally, it is crucial to focus on vulnerable populations, such as the elderly and those with mobility challenges. Transit systems should be designed to be inclusive, ensuring they are both accessible and user-friendly. Features like real-time accessibility information and offline functionality should be prioritized to meet the needs of these groups and promote equitable access to transportation options.

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1. Introduction

Traditional navigation tools like Google Maps primarily optimize for single-trip routes and overlook the complex needs of travelers who require multiple trips or specific modes of travel, particularly individuals with mobility limitations who depend on accessible, multimodal transportation options (Fields et al., 2022). Such individuals face barriers in accessing essential services—such as healthcare, employment, and education—due to the limitations of current navigation systems, which fail to integrate features like trip chaining, elevation information, and options for non-standard mobility modes, thus exacerbating social inequities (Harris et al., 2011; Kaufman et al., 2017). For instance, a study on job accessibility in Canadian cities found that wheelchair users had significantly fewer employment opportunities compared to non-disabled individuals, emphasizing persistent barriers in public transportation systems (Emily et al., 2019).

Equitable mobility solutions are essential to address these disparities, and a multimodal trip-chain planner offers a promising approach to meeting the diverse needs of disadvantaged travelers (Yuan et al., 2023). By incorporating multiple modes—such as public transit, biking, and ridesharing—into a user-centered, activity-based planner, this tool not only optimizes for single trips but also facilitates multiple, coordinated trips across a day. This planner accommodates travel needs such as round trips, coordinated pickups, and socio-recreational activities, which are essential for users balancing various activities throughout the day, especially within vulnerable communities (Bhat and Pendyala, 2005; Huang et al., 2021; Hensher, 2007; Cheng et al., 2016).

Existing studies have suggested activity-based routing approaches (e.g., Chow and Liu, 2012; Luan et al., 2018), but no solution currently integrates comprehensive multimodal trip chain recommendations with intrahousehold travel considerations (Chow and Djavadian, 2015). Such a planner would empower policymakers to develop targeted, revenue-management interventions—such as daily trip thresholds, time-of-day pricing, integrated fares, and group travel discounts—that encourage transit ridership and reduce car dependency, potentially easing congestion and promoting sustainable mobility (Chow, 2014; Pelletier et al., 2011; Dong et al., 2022).

The Multi-Modal Trip-Chain Planner for Disadvantaged Travelers project aims to develop a multimodal trip-chain planner that addresses the specific needs of disadvantaged travelers. This project aligns with the U.S. Department of Transportation's (USDOT) vision of equitable mobility, focusing on reducing transportation inequities and enhancing access for all, regardless of physical or economic circumstances.

The project is designed to improve accessibility and mobility by developing a multimodal trip planner that optimizes multiple trips in a day, integrating various modes of transportation and accommodating group-based travel preferences. The team also focused on understanding microtransit travel patterns in the City of Arlington to train a behavioral model, examining how pricing strategies—such as reduced ride pass prices and place-based subsidies—can increase microtransit use and revenue. In designing solutions for disadvantaged travelers, the project used advanced behavioral models to understand how multimodal planning can improve access and mobility for this community. Additionally, the planner was tested with potential users to ensure its reliability and effectiveness in real-world scenarios. A stated-preference survey was conducted to capture the needs of travelers, revealing significant differences in preferences between rural and urban travelers in North Carolina. Key outputs from this project include an open-source trip-chain planner, behavioral models for Arlington users, survey data that identify the planner's capability in gathering and responding to user needs, and evaluations of revenue management strategies.

The project demonstrated significant potential to transform how disadvantaged travelers access essential services by providing a reliable, user-friendly tool that accommodates multiple modes of transportation and optimizes multiple trips in a day. Its innovative features, such as group-based travel dynamics and collaboration with stakeholders—including local governments, industry partners, and academia—ensured practical, real-world solutions. Key outputs, including open-source tools and behavioral models, were disseminated widely to promote knowledge transfer and adoption. By advancing equitable mobility and aligning with USDOT's research goals, this project has enabled a meaningful impact on transportation for disadvantaged populations.

The rest of the report is broken into two broad chapters: "Chapter 2 Behavioral Modeling" discusses the agent-based behavioral model used for micro transit forecasting and revenue management, and "Chapter 3 on Multimodal Trip-Chain Planner" discusses the design of the trip-chain planner for unique travel needs and the focus group survey conducted for 400 participants in North Carolina. The final "Chapter 4 Summary, Key Findings, and Lessons Learned" presents a synthesis of key findings and directions for future work.

2. Behavioral Modeling

2.1 Introduction

Microtransit can be defined as a shared public or private sector transportation service that offers fixed or dynamically allocated routes and schedules in a demand-responsive manner (Justin Slosky et al. 2022; Volinski et al. 2019). A number of studies have stated that microtransit could improve accessibility by enhancing mobility for underserved populations and transit deserts (Erdoğan et al. 2024), replace fixed-route public transit in lower density and demand areas (Hansen et al. 2021), and relieve traffic congestion by offering shared rides to reduce the number of private vehicles (Kawagughi et al. 2017). The broader market of microtransit services has gained significant interest in various agents because of these promising benefits (Ghimire et al. 2024).

Microtransit is not a "one-size-fits-all" solution in general because its effectiveness depends on the deployment region (Rath et al. 2023). Current microtransit services can be categorized into mixed- or fixed-route microtransit (Via Transportation 2022), first- and last-mile microtransit (Rossetti et al. 2023), and city-wide microtransit (Via Transportation 2024). Compared to the former two categories, city-wide microtransit aims to improve the mobility in cities with little or no existing public transit. With a distance-based trip fare or ride pass subscriptions, residents can summon on-demand, flexible minibuses to their doors and travel to destinations throughout the city (Shaheen et al. 2020). However, diverse travel patterns, heterogeneous user preferences, and limited ground truth data make it challenging to estimate a behavioral model for city-wide microtransit forecasting and revenue management. There are at least three questions that remain to be answered: (1) If only a small proportion of residents use microtransit, how to identify these users and capture heterogeneous tastes in their travel mode choice?; (2) If only marginal subscription data are available for research, how to estimate a choice model that predicts individual-level ride pass subscription?; and (3) If new revenue management policies will be implemented in the future, how to evaluate their potential impacts based on residents' behavioral responses?

To address the current research gap, this study proposes a novel framework that combines synthetic trip data and microtransit usage data to estimate an agent-based behavioral model. The model features a nested structure for travel mode choice and ride pass subscription. First, a lower-branch mode choice model is estimated using synthetic trip data and an agent-based mixed logit (AMXL) approach (Ren and Chow 2022). This model allows agent-specific parameters that reflect residents' heterogenous tastes on microtransit trips. Second, individual-level cost parameters and trip consumer surplus (Bills et al. 2022) are retrieved from the lower branch and integrated into an upper-branch choice model for ride pass subscription. Marginal subscription data are used to calibrate several generic parameters in this model.

Finally, the agent-based, nested model is applied to evaluate ride pass pricing and event- or place-based subsidy policies. Performance metrics include total revenue, total microtransit ridership, total number of subscribers, and total consumer surplus. The proposed framework enables policymakers to consider diverse travel patterns and heterogeneous user preference in the revenue management of city-wide microtransit.

In a case study, we apply this framework to Via microtransit in Arlington, TX. Arlington is one of the largest cities (with 0.4 million residents) in the U.S. with no fixed route public transit. In December 2017, the city launched the first public-private partnership for microtransit as the sole public transportation option, operated by Via. The service expanded incrementally each year, and in 2021 the city entered into an agreement with Via to provide about 70 six-passenger minivans to serve the entire city. This further expanded into an autonomous fleet service around the UT Arlington campus called RAPID. The Via system operating in Arlington offers a unique opportunity to study city-wide microtransit given the maturity and success of the system thus far. Therefore, we built the behavioral model with microtransit usage data from City of Arlington (CoA) and synthetic trip data from Replica Inc. The microtransit usage data was collected in May 2023 and includes marginal information such as daily ridership, daily number of subscribers, average in-vehicle time, and average utilization rate. The synthetic trip data contains trip details made on a typical weekday and weekend in 2023 Q2, including individual ID, trip ID, trip origin and destination, trip start and end time, and travel mode. In the ride pass pricing policy scenario, we aim to find the optimal combination of weekly and monthly ride pass prices that maximizes the total daily revenue. In the event- or place-based subsidy scenario, we focus on trips accessing AT&T Stadium for an event that has the fares subsidized by the event, or access to Medical City Arlington with the hospital subsidizing microtransit trips there. Given a certain discount on microtransit trips, we use the model to predict the changes in car usage and microtransit ridership, as well as the annual subsidy required.

2.2 Literature Review

2.2.1 Concept and Practices of Microtransit Services

Microtransit services, often referred to as an innovative transportation solution, are flexible, IT-enabled public transportation systems that typically use smaller vehicles like shuttles or vans (Hoffmann et al. 2017; Macfarlane et al. 2021). Unlike traditional fixed-route services, microtransit operates on-demand and adjusts routes dynamically based on real-time passenger requests, which are often made through mobile applications (Yan, Levine, and Zhao 2019). This adaptability allows microtransit to serve areas with low transit demand, provide first-mile and last-mile connectivity, and complement existing public transit networks.

The primary benefits of microtransit services include improved accessibility, especially for underserved populations in transit deserts, and enhanced convenience for users by offering door-to-door service

(Erdoğan et al. 2024; Hansen et al. 2021). In suburban and rural areas, microtransit services can be more cost-effective than expanding traditional bus networks, particularly in areas with dispersed demand (Pan and Shaheen 2024). Within urban cores, microtransit can reduce traffic congestion and lower emissions by decreasing the reliance on single-occupancy vehicles (Kawagughi et al. 2017). Moreover, the data-driven nature of microtransit operations enables precise analysis and optimization of routes and schedules, further enhancing efficiency (Veve and Chiabaut 2022). This mode of transportation also supports social equity by providing mobility options to those who may not have access to private vehicles, thus promoting inclusivity in urban mobility systems (Macfarlane et al. 2021; Palm et al. 2021).

Existing microtransit services can be categorized into three types. First, mixed- or fixed-route microtransit is to replace underperforming fixed-route public transit service with flexible on-demand routes (Via Transportation 2022). A real practice is the Hall Area Transit in Gainesville, Georgia. The design of these services is typically formulated as a dynamic vehicle routing problem and has been widely discussed in optimization studies (Fu and Chow 2022; Ma et al. 2021). Second, first- and last-mile microtransit is to extend the reach of pre-existing facilities by improving first- and last-mile connectivity (Rossetti et al. 2023). A real practice is the King County Metro and Sound Transit in Seattle. Research on first- and last-mile microtransit typically entails multimodal travel behavior modeling and accessibility measurement (Liezenga et al. 2024; Truden, Ruthmair, and Kollingbaum 2021). Third, city- or region-wide microtransit is to improve the mobility in areas with little or no existing public transit (Via Transportation 2024). A real practice is in City of Arlington, Texas. Compared to the former two categories, city- or region-wide microtransit serves as a separate transport mode and thus requires a broader range of considerations regarding ridership forecasting, user preferences, revenue management, and equity impacts.

2.2.2 Forecast Models for Microtransit

Simulation-based methods are proven to be effective for evaluating complex mobility systems (Jung and Chow 2019; Markov et al. 2021). Day-to-day adjustment mechanisms have been used to describe a transportation system through its dynamic evolution to capture the equilibrium between demand and mobility services (Watling and Hazelton 2003). Under such mechanisms, users in the system adjust their behavior iteratively each day according to past experiences. These mechanisms involve users iteratively adjusting their behavior daily based on past experiences, allowing the system to evolve and converge to various states depending on initial conditions and user behavior characteristics (Smith et al. 2014). Such models are valuable for representing complex transportation systems, as they explicitly capture the interplay between system state and user behavior.

Djavadian and Chow (2017) proposed an agent-based day-to-day adjustment process for flexible transport services, illustrating that the sampling distribution of different agent populations reaches a stochastic user equilibrium (SUE). This approach allows users to adjust their mode and departure time choices daily to maximize utility and minimize delay, while operators' decisions are integrated into a two-sided market framework. Caros and Chow (2021) extended this model to include operator learning of optimal cost weights to anticipate elastic user demand, specifically evaluating modular autonomous vehicle fleets in Dubai. Rath et al. (2023) proposed a simulation-based scenario data upscaling approach for managing microtransit deployment portfolios, highlighting its potential in microtransit system evaluation.

However, city-wide microtransit is typically treated as a separate mode, considered a substitute for public transit, with its own waiting time, in-vehicle time, and trip fare. For the forecasting and revenue management of city-wide microtransit services, it is reasonable to assume that (1) there is no complex mechanism involving multimodal trips, and (2) intra-individual day-to-day adjustment is less influential than inter-individual taste heterogeneity. To this end, capturing individual decision-making processes and taste heterogeneity across population segments becomes particularly important in scenarios where user preferences, socioeconomic factors, and service characteristics interact in complex ways.

Discrete choice models (DCMs) are widely applied in transportation research to analyze and predict travel behavior by assuming individuals make choices by maximizing the overall utility they can expect to gain (Bowman and Ben-Akiva 2001). These models are essential in our context because they help to understand how various factors, such as travel time, cost, convenience, and individual socio-demographic characteristics influence the decision-making process when selecting among various available mode options, including microtransit (De Vos et al. 2016; Hoffmann et al. 2017). McFadden and Train (2000) presented a mixed logit (MXL) framework that includes any DCMs with discrete choice probabilities to approximate. MXL is a mixture of multinomial logit (MNL) models with random parameters drawn from a probability distribution function, as shown in Equations (1) and (2).

$$U_{nj} = \beta^T X_{nj} + \varepsilon_{nj}\,, \quad \forall n \in N, \forall j \in J \tag{1}$$

$$P_n(j|\theta) = \int \frac{e^{\beta^T X_{nj}}}{\sum_{j' \in J} e^{\beta^T X_{nj'}}}\, g(\beta|\theta) d\beta, \quad \forall n \in N, \forall j \in J \tag{2}$$

where N is the set of individuals and J is the set of alternatives. U_{nj} is the overall utility of individual n choosing alternative j, which consists of a systematic utility $\beta^T X_{nj}$ and a random utility ε_{nj} usually assumed to be independent and identically distributed (i.i.d.). X_{nj} denotes a set of observed attributes of alternative j for individual n. β is a vector of taste parameters assumed to vary randomly across individuals with a probability density $g(\beta|\theta)$, where θ represents the parameters of this distribution (e.g., mean and covariance matrix for normal distribution). Accordingly, the probability of individual n choosing alternative j conditional on θ can be defined as Equation (2).

Though the mixed logit framework allows the distribution of taste parameters to be arbitrary, the mixing distribution is usually restricted to parametric distributions (e.g., normal, uniform, or triangular distribution), which might be problematic when taste heterogeneity deviates from the assumed parametric distribution (Hess 2010). Alternatively, a number of studies proposed semi-parametric or nonparametric approaches to capture taste heterogeneity in a more flexible manner. Fox et al. (2011) proposed a mixture estimator based on linear regression for recovering the joint distribution of taste heterogeneity in DCMs. Train (2016) proposed a logit-mixed logit (LML) model, in which the mixing distribution of parameters can be easily specified using splines, polynomials, step functions, and many other functional forms. Swait (2023) developed a nonparametric approach that combines an upper-level evolutionary algorithm and a lower-level gradient descent algorithm.

Ren and Chow (Ren and Chow 2022) proposed an AMXL approach that is a variant of MXL designed for ubiquitous data sets. They formulated an inverse utility maximization (IUM) problem for an observed choice of an individual (as an agent). The formulation of the IUM problem is shown in Equations (3) and (4), which ensures that the utility derived from a chosen alternative is the highest in the choice set.

$$\min_{\theta_n} \sum_{n \in N} (\theta_0 - \theta_n)^2 \tag{3}$$

subject to:

$$\theta_n^T X_{nj^*} + \varepsilon_{nj^*} \geq \theta_n^T X_{nj} + \varepsilon_{nj} + b, \qquad \forall n \in N, j \in J, j \neq j^* \tag{4}$$

where θ_0 is a vector of prior taste parameters; θ_n is a vector of posterior taste parameters for agent n; X_{nj} is a vector of alternative attributes; $\theta_n^T X_{nj}$ is the systematic utility derived from agent n choosing alternative j; ε_{nj} is the random utility that is Gumbel distributed; b is a safe boundary in case ε_{nj^*} is much larger than ε_{nj} in a single draw (making the comparison of systematic utilities meaningless). This approach captures heterogeneous user preferences by estimating agent-specific parameters, which provides new opportunities for estimating residents' responses to various microtransit policies.

2.2.3 Current Research Gap

Despite the flood of innovative ideas, estimating a behavioral model for microtransit forecasting and revenue management is challenging for two reasons. First, currently, only a small proportion of residents use microtransit services, but their potential impacts on all trips made by the total population need to be considered. Second, due to data privacy issues, only marginal microtransit data (e.g., daily ridership, daily number of subscribers, average in-vehicle time, etc.) are available for analysis, making it even infeasible to build a simple regression model. These challenges call for a combination of ground truth "thick data," emerging "big data," and advanced choice modeling techniques.

In the case of city-wide microtransit, at least three questions remain unanswered. First, if only a small proportion of residents use microtransit, how can these users be identified, and how can heterogeneous tastes in their travel mode choices be captured? Second, if only marginal subscription data are available for research, how can a choice model that predicts individual-level ride pass subscriptions be estimated? Finally, if new revenue management policies will be implemented in the future, how can their potential impacts be evaluated based on residents' behavioral responses? Answering these questions requires a novel framework that combines synthetic trip data, microtransit usage data, and the AMXL approach to estimate an agent-based, nested behavioral model.

2.3 Proposed Methodology

We propose a general framework that takes synthetic trip data and microtransit usage data as inputs and outputs an agent-based, nested behavior model to support city-wide microtransit design. The scope of our methodology is shown in Figure 2.1, which consists of initial settings and three major parts: (1) lower-branch mode choice modeling; (2) upper-branch ride pass subscription modeling; and (3) scenario design and evaluation based on the behavior model.

2.3.1 Problem Statement

We separate choice related to microtransit into two parts: travel mode choice and ride pass subscription choice. In travel mode choice, individuals decide on mode to use by considering factors such as travel time, cost, trip purpose, tour type, and mode-specific preferences. The mode choice set includes traditional modes (e.g., driving, walking, biking, etc.) and microtransit. In ride pass subscription choice, individuals decide whether to purchase a weekly ride pass, a monthly ride pass, or no ride pass at all. By subscribing to a ride pass, travelers pay an amount of money in advance and enjoy free microtransit trips until the ride pass expires. Accordingly, the cost of the ride pass and the utility gained from free microtransit trips after subscribing can influence their decisions.

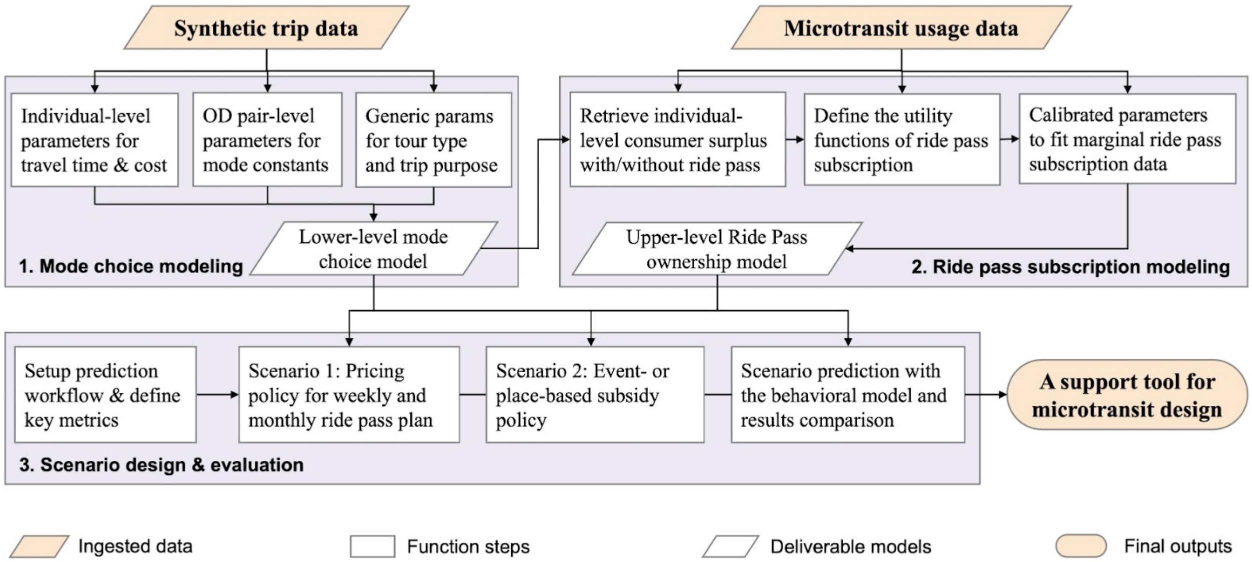


Figure 2.1: Proposed framework

Hence, we formulate a nested structure for microtransit behavioral choice (Figure 2.2). The lower branch is a travel mode choice model that takes trip-level data as inputs. Considering the heterogeneous tastes across different regions and population segments, this model is estimated with large-scale synthetic trip data and the AMXL approach. The upper branch is a ride pass subscription model that takes individual-level parameters and expected utilities from the lower branch as inputs. Since only marginal subscription data is available for model estimation, we treat it as a MNL model and calibrate only several parameters to fit observed figures.

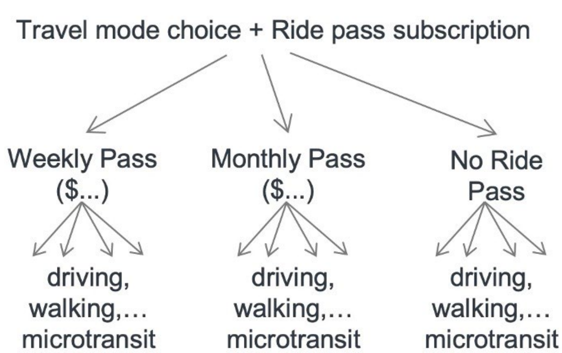


Figure 2.2. The nest structure of microtransit behavioral choice.

2.3.2 Lower-branch mode choice model

Model Specification

We consider five different modes, including driving, biking, walking, carpool (several passengers sharing one private vehicle), and microtransit. Public transit is excluded from the mode choice set since we focus on the city-wide microtransit case. For each trip t made by individual n along origin-destination (OD) pair uw, the utilities and probabilities of choosing these five modes are defined in Equations (5) to (11).

$$V_{driving,t} = asc_{driving,uw} + \beta_{tt_{auto},n} \times TT_{driving,t} + \beta_{cost,n} \times CO_{driving,t}, \qquad \forall t \in T \tag{5}$$

$$V_{bike,t} = asc_{bike,uw} + \beta_{tt_{non-auto},n} \times TT_{bike,t}, \qquad \forall t \in T \tag{6}$$

$$V_{walk,t} = asc_{walk,uw} + \beta_{tt_{non-auto},n} \times TT_{walk,t}, \qquad \forall t \in T \tag{7}$$

$$V_{carpool,t} = \beta_{tt_{auto},n} \times TT_{carpool,t} + \beta_{cost,n} \times CO_{carpool,t}, \qquad \forall t \in T \tag{8}$$

$$\begin{aligned} V_{MT,t} = asc_{MT,uw} &+ \beta_{tt_{auto},n} \times TT_{MT,t} + \beta_{wt,n} \times WT_{MT,t} + \beta_{cost,n} \times CO_{MT,t} \\ &+ \beta_{p_{shopping}} \times PSH_t + \beta_{p_{school}} \times PSC_t + \beta_{p_{other}} \times POT_t \\ &+ \beta_{t_{commute}} \times TCO_t + \beta_{t_{work}} \times TWO_t, \qquad \forall t \in T \end{aligned} \tag{9}$$

$$U_{j,t} = V_{j,t} + \varepsilon_{j,t}, \qquad \forall t \in T, j \in J \tag{10}$$

$$P_{j,t} = \frac{e^{V_{j,t}}}{\sum_{k \in J} e^{V_{k,t}}}, \qquad \forall t \in T, j \in J \tag{11}$$

where $t \in T$ is the unique index of trips made by all individuals along all OD pairs. $V_{driving,t}, \dots, V_{MT,t}$ are systematic utilities, in which variables and parameters in these utility functions are defined in Table 2.1. $U_{j,t}$ is the total utility of choosing mode j in trip t, $\varepsilon_{j,t}$ is a Gumbel-distributed random utility, and $P_{j,t}$ is the choice probability. $J = \{driving, bike, walk, carpool, MT\}$ is the mode choice set. For the utility of microtransit, we add several interaction items to consider the effects of tour type and trip purpose.

Notation	Description
Travel time and cost variables	
$\boldsymbol{TT_{j,t}}$	Travel time (min) of trip $\boldsymbol{t}$ using mode $\boldsymbol{j} \in \{\boldsymbol{driving}, \boldsymbol{bike}, \boldsymbol{walk}, \boldsymbol{carpool}, \boldsymbol{MT}\}$
$\boldsymbol{WT_{MT,t}}$	Microtransit waiting time (min) of trip $\boldsymbol{t}$
$\boldsymbol{CO_{j,t}}$	Travel monetary cost ($) of trip $\boldsymbol{t}$ using mode $\boldsymbol{j} \in \{\boldsymbol{driving}, \boldsymbol{carpool}, \boldsymbol{MT}\}$
Trip purpose and tour type dummy variables	
$\boldsymbol{PSH_t}$	=1 if the purpose of trip $\boldsymbol{t}$ is shopping, otherwise =0
$\boldsymbol{PSC_t}$	=1 if the purpose of trip $\boldsymbol{t}$ is school, otherwise =0
$\boldsymbol{POT_t}$	=1 if the purpose of trip $\boldsymbol{t}$ is others, otherwise =0
	Trip purpose 'home' is set as the reference level

$\boldsymbol{TCO_t}$	=1 if the tour type of trip $\boldsymbol{t}$ is commute, otherwise =0
$\boldsymbol{TWO_t}$	=1 if the tour type of trip $\boldsymbol{t}$ is work-based, otherwise =0
	Tour type 'home-based' is set as the reference level
Individual-specific parameters	
$\boldsymbol{\beta_{tt_{auto},n}}$	Auto travel time parameter of individual $\boldsymbol{n}$
$\boldsymbol{\beta_{tt_{non-auto},n}}$	Non-auto travel time parameter of individual $\boldsymbol{n}$
$\boldsymbol{\beta_{wt,n}}$	Microtransit waiting time parameter of individual $\boldsymbol{n}$
$\boldsymbol{\beta_{cost,n}}$	Travel cost parameter of individual $\boldsymbol{n}$
OD-pair specific parameters	
$\boldsymbol{asc_{driving,uw}}$	Alternative specific constant of driving on OD pair $\boldsymbol{uw}$
$\boldsymbol{asc_{bike,uw}}$	Alternative specific constant of bike on OD pair $\boldsymbol{uw}$
$\boldsymbol{asc_{walk,uw}}$	Alternative specific constant of walk on OD pair $\boldsymbol{uw}$
$\boldsymbol{asc_{MT,uw}}$	Alternative specific constant of microtransit on OD pair $\boldsymbol{uw}$
	Carpool is set as the reference level
Generic parameters	
$\boldsymbol{\beta_{p_{shopping}}}$	Generic parameter of trip purpose 'shopping'
$\boldsymbol{\beta_{p_{school}}}$	Generic parameter of trip purpose 'school'
$\boldsymbol{\beta_{p_{other}}}$	Generic parameter of trip purpose 'other'
$\boldsymbol{\beta_{t_{commute}}}$	Generic parameter of tour type 'commute'
$\boldsymbol{\beta_{t_{work}}}$	Generic parameter of tour type 'work-based'

Table 2.1. Variables and parameters in the mode choice model.

Different from traditional mode choice models, we allow time and cost parameters to vary across individuals (with index n), and we allow mode specific constants to vary across trip OD pairs (with index uw). This makes sense when we do not have sufficient data for socioeconomic attributes and built environment variables. The assumption we made here is that the impacts of these unobserved variables are included in the nonparametric distribution of individual and OD pair-level parameters. This is only possible with synthetic trip data and the AMXL approach.

Estimation algorithm

Synthetic trip data is a type of ubiquitous dataset generating by combining census data, travel survey data, and large-scale information and communication technology (ICT) data (Replica Inc., 2024). With such a dataset, it is unnecessary to assume a parametric distribution to transfer from a sample to the total population, as the sample size is sufficiently large. The AMXL approach is a variant of mixed logit (MXL) for estimating agent-specific parameters from a ubiquitous dataset. Following Ren and Chow (2022)'s work, we treat each trip as an agent and formulate a multi-agent inverse utility maximization problem (MIUM) for travel mode choice, as shown in **Equations (12) to (18)**.

$$\min_{\beta_{k,0},\beta_{k,t}} \sum_{k\in K}\sum_{t\in T}(\beta_{k,0}-\beta_{k,t})^2 \tag{12}$$

subject to:

$$V_{j^*,t}(\beta_t)+\varepsilon_{j^*,t} \geq V_{j,t}(\beta_t)+\varepsilon_{j,t}+b, \qquad \forall t\in T, j, j^*\in J, j\neq j^* \tag{13}$$

$$\beta_{k,t} \geq lb, \qquad \forall t\in T, k\in K \tag{14}$$

$$\beta_{k,t} \leq ub, \qquad \forall t\in T, k\in K \tag{15}$$

$$\beta_{k,n} = \frac{1}{|T_n|}\sum_{t\in T_n}\beta_{k,t}\,, \qquad \forall n\in N, k\in K_N \tag{16}$$

$$\beta_{k,uw} = \frac{1}{|T_{uw}|}\sum_{t\in T_{uw}}\beta_{k,uw}\,, \qquad \forall u\in O, w\in D, k\in K_{uw} \tag{17}$$

$$\beta_{k,0} = \frac{1}{|T|}\sum_{t\in T}\beta_{k,t}\,, \qquad \forall k\in K \tag{18}$$

where $\beta_{k,0}$ is the k^{th} parameter in the fixed-point prior (generic parameter); $\beta_{k,t}$ is the k^{th} parameter specific to trip t; $\beta_{k,n}$ is the k^{th} parameter specific to individual n; $\beta_{k,uw}$ is the k^{th} parameter specific to OD pair uw. Equation (13) ensures that in each trip t the chosen alternative j^* has the highest total utility in the choice set J. Equations (14) to (15) determine the parameter boundary for estimation, in which lb and ub specifies the lower and upper boundaries. Equation (16) to (17) are proposed by our study, which ensure some parameters vary across individuals and OD pairs (without these constraints all parameters will vary across trips, increasing the risk of overfitting). Equation (18) ensures that generic parameters come from the mean value of agent-specific parameters.

It is noted that solving the MIUM problem as a single quadratic programming (QP) problem would be computationally costly as it would lead to a highly sparse diagonal matrix. Instead, we use a decomposition method to initialize $\beta_{k,0}$ and update $\beta_{k,0}, \beta_{k,n}, \beta_{k,uw}$ iteration by iteration. The whole estimation approach is summarized in Algorithm 2.1.

Algorithm 2.1. Parameter estimation for AMXL

---

1. Given observed variables and mode choice, initialize with $i = 0, b = 1$, and the fixed-point priors $\beta_{k,0}^{(i)} = 0, \forall k \in K$.
2. For each trip $t \in T$, solve a QP problem get $\beta_{k,t}^{(i)}$:
   $\min_{\beta_{k,0},\beta_{k,t}} \sum_{k\in K}\sum_{t\in T}(\beta_{k,0} - \beta_{k,t})^2$ subject to constraints in Equations (13) to (15).
3. Calculate individual-specific parameters ($\beta_{k,n}$) and OD pair-specific parameters ($\beta_{k,uw}$) using Equations (16) to (17).
4. Set average to $y_k^{(i)}$=$\sum_{t\in T}\beta_{k,t}^{(i)}$, $\forall k \in K$ as shown in Equation (18).
5. Using Method of Successive Average to update the fixed-point prior and get $\beta_{k,0}^{(i+1)}$:
   $$\beta_{k,0}^{(i+1)} = \frac{n}{n+1}\beta_{k,0}^{(i)} + \frac{1}{n+1}y_k^{(i)}, \qquad \forall k \in K$$
6. If the stopping criteria for $\beta_{k,0}$ reached, stop and output $\beta_{k,0}^{(i)}, \beta_{k,n}^{(i)}, \beta_{k,uw}^{(i)}$; else, set $i = i + 1$ and go back to Step 2.

2.3.3. Upper-branch ride pass subscription model

Model specification

We consider three alternatives, including purchasing weekly ride pass, purchasing monthly ride pass, and purchasing no ride pass at all. Their systematic utilities are defined in Equations (19) to (21).

$$V_{weekly,n} = COST_{weekly} \times \beta_{cost_{RP}} \times \beta_{cost,n} + \beta_{cv_{weekday}} \times CV_{wd,n} + \beta_{cv_{weekend}} \times CV_{we,n} + \beta_{MT-user} \times MT_n + asc_{weekly}, \qquad \forall n \in N \tag{19}$$

$$V_{monthly,n} = COST_{monthly}/4 \times \beta_{cost_{RP}} \times \beta_{cost,n} + \beta_{cv_{weekday}} \times CV_{wd,n} + \beta_{cv_{weekend}} \times CV_{we,n} + \beta_{MT-user} \times MT_n + asc_{monthly}, \qquad \forall n \in N \tag{20}$$

$$V_{none,n} = 0, \qquad \forall n \in N \tag{21}$$

the utility of purchasing a ride pass consists of four components: (1) the utility related to the prices of ride passes, where $COST_{weekly}$, $COST_{monthly}$ are the prices of weekly and monthly ride passes, respectively ($COST_{monthly}$ is divided by 4 to calculate the utility gained per week), $\beta_{cost,n}$ is the cost parameter from the lower-branch mode choice model, and $\beta_{cost_{RP}} > 0$ is a transfer factor from trip fare to ride pass price; (2) the utility related to the change in consumer surplus (or compensating variation) brought by free microtransit trips with a ride pass, where $CV_{wd,n}$ and $CV_{we,n}$ denote individual n's compensating variation on weekdays and weekends, and $\beta_{cv_{weekday}}$, $\beta_{cv_{weekend}}$ are their parameters; (3) the utility specific to microtransit users, where MT_n is a binary variable indicating whether individual n has observed microtransit trips, and $\beta_{MT-user}$ is its parameter; and (4) the alternative specific constant of the ride pass,

asc_{weekly} and $asc_{monthly}$. $CV_{wd,n}$ and $CV_{we,n}$ can be retrieved from the lower branch, as shown in Equation (22).

$$CV_{d,n} = \sum_{t \in T_{d,n}} \left(\ln \sum_{j \in J} e^{V'_{j,t}} \right) - \sum_{t \in T_{d,n}} \left(\ln \sum_{j \in J} e^{V_{j,t}} \right), \qquad \forall n \in N, d \in \{we, wd\} \tag{22}$$

where $d \in \{we, wd\}$ indicates the day of week, $T_{d,n}$ is the set of trips made by individual per weekday/weekend. The difference between $V'_{j,t}$ and $V_{j,t}$ is that in $V'_{MT,t}$ the trip fare of microtransit is zero due to ride pass subscription. It is noted that $\beta_{cost,n}$, $CV_{wd,n}$, $CV_{we,n}$, and MT_n are individual-level details from the lower branch, which could 'enhance' the ride pass subscription modeling with only marginal data available.

Estimation Algorithm

Given the data availability, we consider the ride pass model as a simple MNL model with six parameters to calibrate ($\beta_{cost_{RP}}$, $\beta_{cv_{weekday}}$, $\beta_{cv_{weekend}}$, $\beta_{MT-user}$, asc_{weekly}, $asc_{monthly}$). These ride pass parameters are calibrated using the Nelder-Mead Simplex Method (McKinnon 1998). The cost function to minimize is the squared distance between the predicted ride pass market share and the observed one.

2.3.4 Scenario design and policy evaluation

Once the nested behavior model has been estimated, residents' response to microtransit policies can be evaluated based on the model prediction. We consider two policy scenarios: (1) the scenario of ride pass pricing policies and (2) the scenario of event- or place-based subsidy policy.

The first scenario involves setting fixed prices for weekly and monthly ride passes, allowing users to pay upfront for unlimited rides within the subscription period. This scenario aims to find ideal price combinations that can encourage ridership and ride pass subscription, create revenue, and increase consumer surplus. The second scenario involves financial incentives, such as discounted or free rides, for trips associated with specific events or destinations. This scenario aims to predict the effects on reducing congestion, promoting public transportation use during high-demand periods, and making transit options more attractive and accessible for attendees or visitors to these locations. Several performance metrics are retrieved from the model prediction for policy evaluation, including:

- **Microtransit ridership:** we calculate microtransit ridership by summing up the trip-level probability of choosing microtransit. To obtain the daily microtransit ridership (trips/day), we average weekday ridership and weekday ridership based on the number of days in a week.

- **Number of ride pass subscribers:** we calculate the number of ride pass subscribers (subscribers/day) by summing up the individual-level probability of purchasing weekly and monthly plans.

- **Total revenue:** total revenue ($/day) consists of the revenue collected from trip fare and the revenue collected from ride pass subscription. To calculate trip fare revenue, we only consider microtransit trips made by non-subscribers. To obtain the daily ride pass revenue, we divide weekly ride pass revenue by 7, monthly ride pass revenue by 30, and add them together.

- **Total consumer surplus:** we calculate the total consumer surplus using the expected utility of the upper-branch choice set (Bills et al. 2022). The parameter of trip cost is used to transfer the unit of consumer surplus into dollars.

2.4 Case study: Via Microtransit in Arlington, TX

In this section, we apply the proposed framework to a case study in Arlington, TX. Arlington, with a population of 400,000, is one of the largest U.S cities without a traditional public transit system. In December 2017, Arlington launched the first public-private partnership for microtransit, making it the city's sole public transit option, operated by Via. The service has expanded annually, and in 2021, the city contracted Via to operate approximately 70 six-passenger minivans covering the entire city. The established Via system in Arlington generated valuable ground truth data to analyze city-wide microtransit.

All of the experiments are conducted on a local machine with Intel(R) Core(TM) i7-10875H CPU and 32GB installed RAM. The Gurobi package is used to solve the QP problems. Codes are written in Python.

2.4.1 Data collection

Synthetic trip data from Replica Inc.

The synthetic trip dataset provided by Replica Inc. comprises 1.3 million trips made by 0.4 million Arlington residents on a typical weekday and weekend in 2023 Q2. Trip details include the origin and destination, trip mode, trip distance, trip duration, and trip cost. The dataset was generated through a combination of mobile location data, resident data, built environment data, and economic activity data. The data quality report is available at the census level for the whole U.S. region (Replica Inc. 2022), in which the largest error of demographic attributes for a single census tract unit is within 5% compared to census data, and the largest error of commute mode share for a single census tract unity is within 10% compared to Census Transportation Planning Products (CTPP) data. Figure 3.3 shows census block group-level OD pairs with more than 50 trips/day, from which we can see diverse travel patterns made by different population segments. The synthetic trip data in Arlington includes five modes: driving, biking, walking, carpool, and on-demand auto. Based on the mode share, we treat on-demand auto trips as microtransit trips (accounting for 0.4% of the total trips).

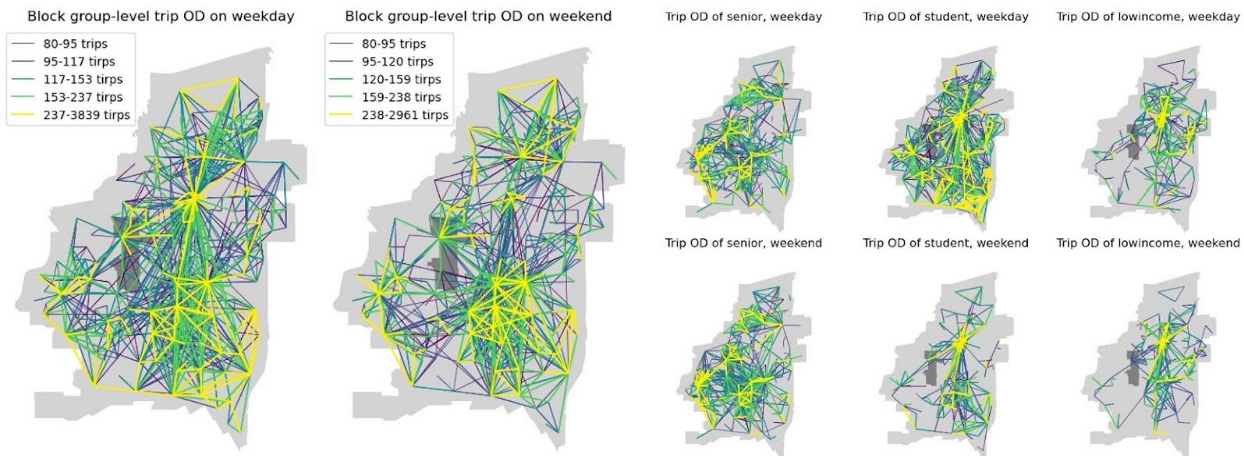
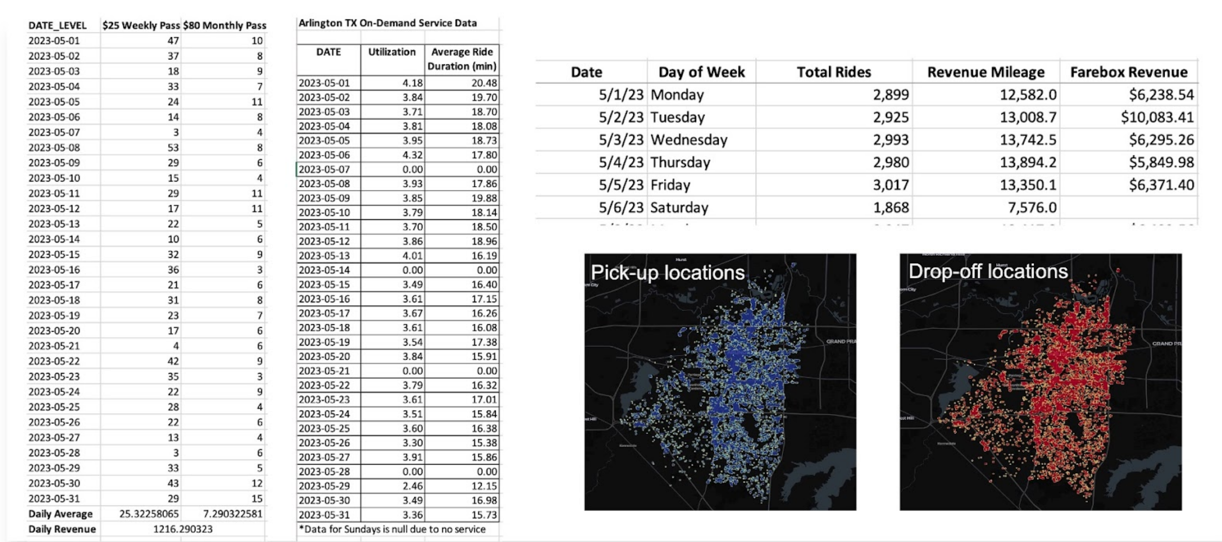


Figure 2.3. Block group-level trip OD pairs retrieved from Replica's data.

Microtransit usage data from City of Arlington (CoA)

Microtransit usage data from CoA include marginal information on daily ridership, daily number of subscribers, average in-vehicle time, average utilization rate, and heatmaps of pick-up and drop-off locations (Figure 2.4). Due to data privacy issues, only marginal figures are available for analysis, but they are still useful to calibrate parameters in the ride pass subscription model.



DATE_LEVEL	$25 Weekly Pass	$80 Monthly Pass
2023-05-01	47	10
2023-05-02	37	8
2023-05-03	18	9
2023-05-04	33	7
2023-05-05	24	11
2023-05-06	14	8
2023-05-07	3	4
2023-05-08	53	8
2023-05-09	29	6
2023-05-10	15	4
2023-05-11	29	11
2023-05-12	17	11
2023-05-13	22	5
2023-05-14	10	6
2023-05-15	32	9
2023-05-16	36	3
2023-05-17	21	6
2023-05-18	31	8
2023-05-19	23	7
2023-05-20	17	6
2023-05-21	4	6
2023-05-22	42	9
2023-05-23	35	3
2023-05-24	22	9
2023-05-25	28	4
2023-05-26	22	6
2023-05-27	13	4
2023-05-28	3	6
2023-05-29	33	5
2023-05-30	43	12
2023-05-31	29	15
Daily Average	25.32258065	7.290322581
Daily Revenue	1216.290323	

Arlington TX On-Demand Service Data

DATE	Utilization	Average Ride Duration (min)
2023-05-01	4.18	20.48
2023-05-02	3.84	19.70
2023-05-03	3.71	18.70
2023-05-04	3.81	18.08
2023-05-05	3.95	18.73
2023-05-06	4.32	17.80
2023-05-07	0.00	0.00
2023-05-08	3.93	17.86
2023-05-09	3.85	19.88
2023-05-10	3.79	18.14
2023-05-11	3.70	18.50
2023-05-12	3.86	18.96
2023-05-13	4.01	16.19
2023-05-14	0.00	0.00
2023-05-15	3.49	16.40
2023-05-16	3.61	17.15
2023-05-17	3.67	16.26
2023-05-18	3.61	16.08
2023-05-19	3.54	17.38
2023-05-20	3.84	15.91
2023-05-21	0.00	0.00
2023-05-22	3.79	16.32
2023-05-23	3.61	17.01
2023-05-24	3.51	15.84
2023-05-25	3.60	16.38
2023-05-26	3.30	15.38
2023-05-27	3.91	15.86
2023-05-28	0.00	0.00
2023-05-29	2.46	12.15
2023-05-30	3.49	16.98
2023-05-31	3.36	15.73

*Data for Sundays is null due to no service

Date	Day of Week	Total Rides	Revenue Mileage	Farebox Revenue
5/1/23	Monday	2,899	12,582.0	$6,238.54
5/2/23	Tuesday	2,925	13,008.7	$10,083.41
5/3/23	Wednesday	2,993	13,742.5	$6,295.26
5/4/23	Thursday	2,980	13,894.2	$5,849.98
5/5/23	Friday	3,017	13,350.1	$6,371.40
5/6/23	Saturday	1,868	7,576.0	

Figure 2.4. A screenshot of microtransit usage data from CoA.

Simulated microtransit waiting time and in-vehicle time

Since Replica's data does not separate microtransit waiting time and in-vehicle time (only has total travel time), we use a simulation tool NOMAD-RPS (Namdarpour et al. 2024) to obtain simulated microtransit performance. The simulator takes trip requests and service parameters as input and output trip-level microtransit travel and waiting time. Service parameters are calibrated using a grid search approach to fit data from CoA, such as maximum walking time (12 minutes), maximum waiting time (40 min), ratio of waiting and travel value of time (1.0), the weight of operating cost (0.2), and the weight of looking ahead value (0.05). Table 2.2 shows a comparison between simulation results and ground truth data. The simulated average in-vehicle travel time is slightly longer than observed, while the simulated utilization rate is slightly lower than observed. The largest percentage difference is approximately 15%, which is acceptable.

	Simulation results	Data from CoA	% Difference
Average in-vehicle time (weekday)	19.99 min	17.31 min	15.48%
Average in-vehicle time (weekend)	18.76 min	16.44 min	14.12%
Average utilization rate (weekday)	3.467	3.637	-4.67%
Average in-vehicle time (weekend)	3.682	4.017	-8.34%
Average waiting time (weekday)	14.11 min	12-15 min	--
Average waiting time (weekend)	11.71 min	12-15 min	--

Table 2.2. A comparison between simulation results and ground truth data.

Note: utilization rate is calculated as the average number of served passengers per vehicle per hour.

2.4.2 Results of the behavioral model

The lower-branch mode choice model

Table 2.3 compares the estimation results of MNL, nest logit (NL), and AMXL for travel mode choice. MXL failed to converge with the whole samples (~0.7 million choice observations) in our experiments. Several interesting points were found.

- Besides parameters for trip purpose and tour type, most parameters are significant at 1% level. Weekday and weekend models show slight difference in parameter signs and magnitudes.
- Though MNL and NL get acceptable goodness-of-fit, parameters of microtransit waiting time and travel cost have positive signs, resulting in unreasonable elasticity for further policy evaluation.
- The computing time of AMXL is obviously longer than MNL and NL, but AMXL obtains better results. With agent-level constraints in AMXL, parameters of waiting time and travel cost are

bounded to be negative, and the agent-specific parameters result in higher McFadden R-square compared to MNL and NL.

	MNL		NL		AMXL	
	Weekday	**Weekend**	**Weekday**	**Weekend**	**Weekday**	**Weekend**
Travel time and cost						
Auto travel time	-0.001	-0.002***	-0.001**	0.275***	-0.205	-206
(tt auto,n)	-0.001	-0.0006	-0.0003	-0.004		
Non-auto travel time	-0.077***	-0.096***	-0.021***	0.922***	-0.304	-0.331
(tt non-auto,n)	-0.001	-0.001	-0.006	-0.021		
Microtransit waiting time	0.238***	0.206***	0.238***	0.091***	-0.297	-0.3
(wt,n)	-0.01	-0.01	-0.004	-0.03		
Travel cost	0.466***	-0.295***	0.149***	-0.435***	-0.743	-0.752
(cost,n)	-0.02	-0.019	-0.043	-0.051		
Mode specific constant						
Driving constant	0.803***	1.018***	0.221***	2.224***	2.07	2.301
(ascdriving,uw)	-0.004	-0.004	-0.064	-0.222		
Biking constant	-2.266***	-2.756***	-0.638***	-0.822***	-2.621	-2.553
(ascbike,uw)	-0.015	-0.02	-0.185	-0.672		
Walking constant	0.998***	0.985***	0.275***	0.753***	1.584	0.91
(ascwalk,uw)	-0.009	-0.011	-0.08	-0.203		
Microtransit constant	-9.084***	-5.605***	-8.777***	-5.436***	-0.349	-0.414
(ascMT,uw)	-0.205	-0.26	-0.148	-0.495		
Tour type and trip purpose						
Purpose: shopping	-0.087	-0.342	-0.158	-0.356	-0.379	-0.611
(p shopping)	-0.151	-0.223	-0.15	-0.242		
Purpose: school	-0.032	0.16	-0.127	0.445	-0.906	-0.065
(p school)	-0.203	-0.378	-0.203	-0.387		
Purpose: other	0.238	0.075	0.201	0.055	-0.678	-0.714
(p other)	-0.139	-0.219	-0.138	-0.238		
Tour type: commute	-2.372***	-1.472***	-2.366***	-1.282***	-0.916	-0.424
(t commute)	-0.121	-0.213	-0.122	-0.237		
Tour type: work-based	-0.838***	0.131	-0.847***	0.332	-0.451	-0.718
(t work)	-0.11	-0.203	-0.106	-230		
Meta information						
# Observations	699,995	646,784	699,995	646,784	699,995	646,784
Estimation time	58 s	46 s	2 min 37 s	2 min 53 s	9.00 h	7.90 h
McFadden R-square	0.479	0.519	0.48	0.52	0.603	0.576

Table 2.3. Estimation results of MNL, NL, and AMXL for travel mode choice.

Notes: Each entry represents the average value of one estimated parameter, and the number in parenthesis is the standard error.

****p-value<0.001, **p-value<0.01, *p-value<0.05*

Figures 2.5 and 2.6 show estimation details of the weekday model and weekend model. The algorithm converged within 30 iterations, resulting in calibrated parameters that are empirically derived, revealing them to be neither Gumbel nor Gaussian. Instead, the empirical distribution seems to be a combination of a constant (assumed in MNL) and Gaussian distribution (assumed in MXL). Moreover, the value of travel time is about $14 per hour, the value of waiting time is about $25 per hour. These also align with our expectations.

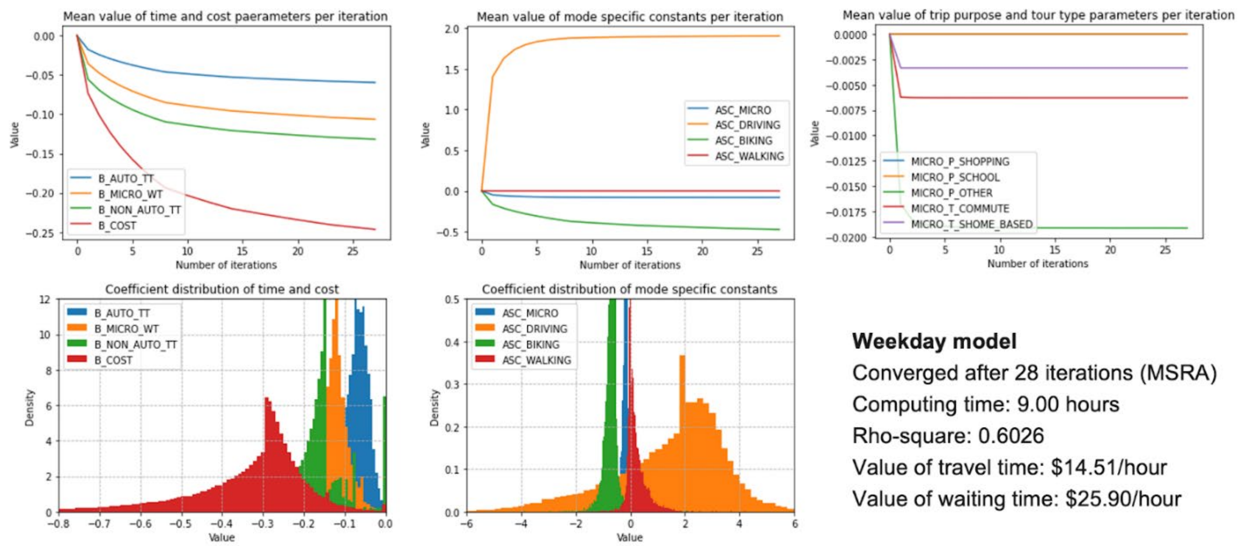


Figure 2.5. Estimation details of the weekday model.

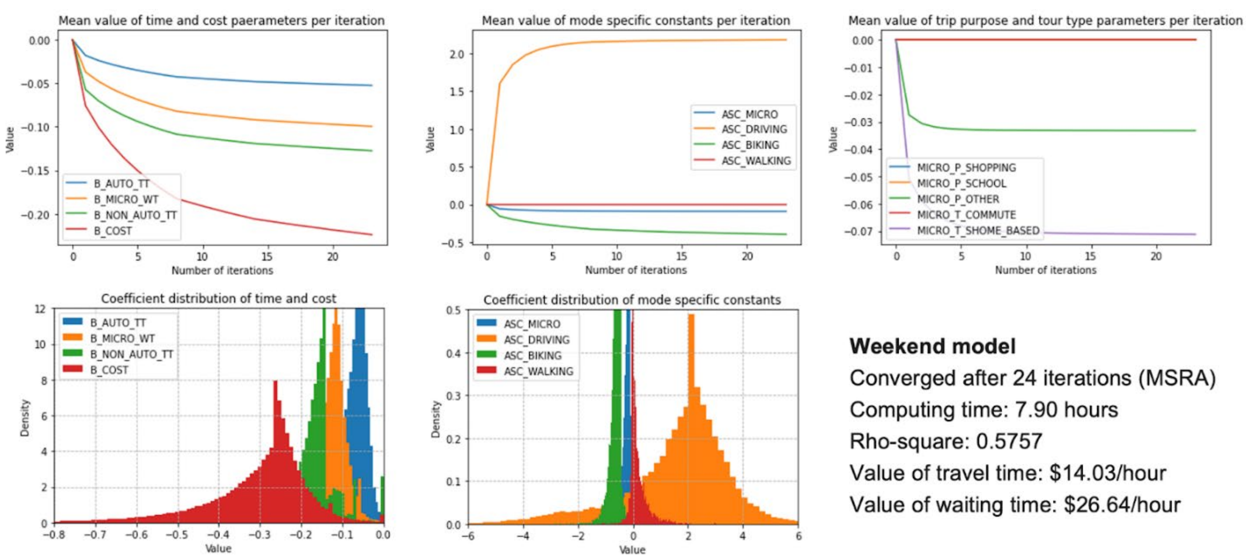


Figure 2.6. Estimation details of the weekend model.

The upper-branch ride pass subscription model

Table 2.4 shows the calibration results of the upper-branch ride pass subscription model. The predicted proportions of individuals with ride pass subscription are exactly the same as observed ones. Moreover, we also find some interesting points from the prediction results: (1) The predicted number of subscribers and ride pass revenue are close to the real values; (2) We can further plot the number of subscribers per block group on the map; (3) Most of the predicted subscribers (392/412) have used microtransit service before; and (4) The probability of ride pass subscribers' using microtransit (20.07%) is obviously higher than the probability of non-subscribers (0.46%). These details are useful in the scenario simulation.

$\beta_{\text{cost RP}}$	$\beta_{\text{CV weekday}}$	$\beta_{\text{CV weekend}}$	$\beta_{\text{MT-user}}$	asc_{weekly}	asc_{monthly}
0.945	4.284	2.345	7.939	-1.549	-2.34
Ground truth ride pass proportion					
Weekly ride pass: 0.0943%	Monthly ride pass: 0.1163%	No ride pass: 99.7894%			
Predicted ride pass proportion					
Weekly ride pass: 0.0943%	Monthly ride pass: 0.1163%	No ride pass: 99.7894%			

Table 2.4. Calibration results of the ride pass subscription model.

2.4.3 Revenue management policy evaluation

Scenario 1: Ride pass pricing policy

The first scenario examines the impact of increasing or decreasing the prices of the current ride pass plans. Figure 2.7 shows the optimal price combination for maximizing total daily revenue. Our prediction results indicate that to maximize total revenue, which includes income from trip fares and ride pass subscriptions, the price of the weekly ride pass should decrease from $80 to $71.5. This adjustment would result in a $102 increase in total daily revenue.

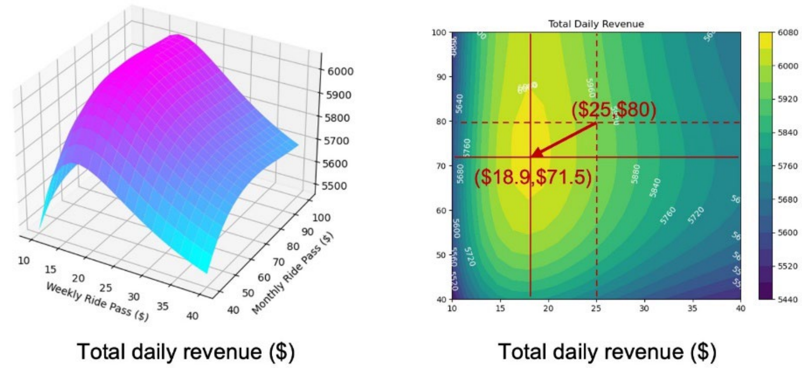


Figure 2.7. Best price combination to maximize total daily revenue.

If we aim to consider both the total daily revenue and total trip consumer surplus, meaning we want to maximize the combined benefits for operators and travelers, the price of the weekly ride pass should decrease from $25 to $13.1, and the price of the monthly ride pass should decrease from $80 to $49.4 (Figure 2.8). This significant discount balances the benefits between operators and travelers, increasing the total value by $363 per day.

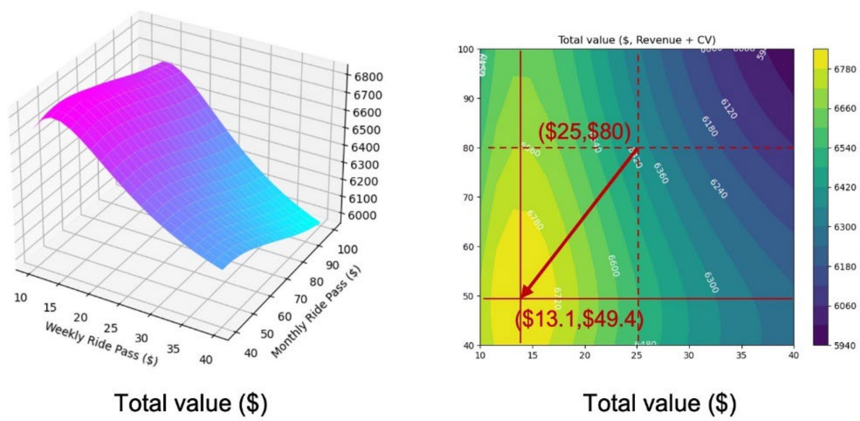


Figure 2.8. Best price combination to maximize total daily revenue + total consumer surplus.

Scenario 2: Event- or place-based subsidy policy

The second scenario involves an event- or place-based subsidy policy, which aims to reduce car use or improve access to facilities by partnering with the place or event to have them offer a subsidy to support a discount on microtransit trip fares. Based on our model, we predict the effects of a specific discount and estimate the amount of subsidy required. The subsidy could be provided by the government or facility stakeholders.

For event-based policy, we consider trips that start from or end at AT&T Stadium, which is home of the Dallas Cowboys (Figure 2.9). The prediction results show that if we focus on peak hours on weekends (time for sport events), a 100% fare discount on trips going to and departing from AT&T Stadium could reduce driving proportion from 61.3% to 59.2% (~80 car trips per day during peak period), but it would require a subsidy of $617 per day ($32,068 per year). This gives Arlington a way to promote the microtransit, increase awareness with marketing, and offer the stadium an opportunity to be more sustainable in their operations.

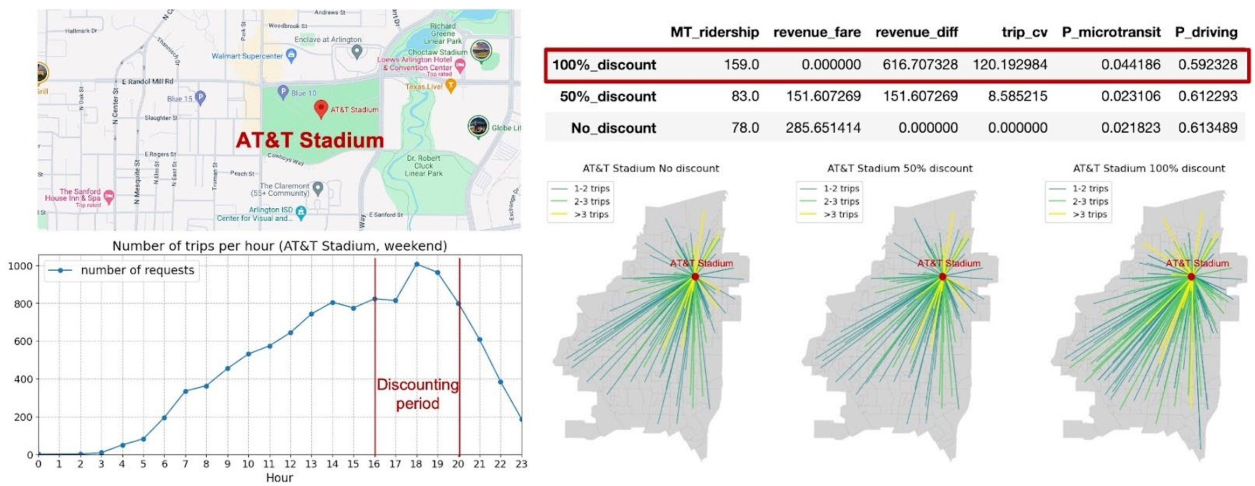
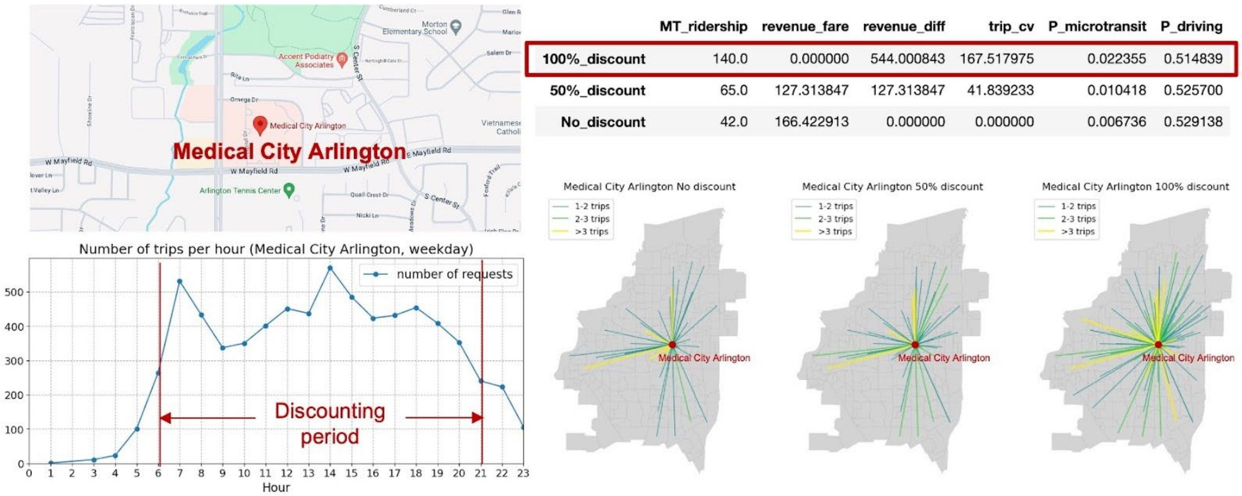


Figure 2.9. Event-based subsidy policy for AT&T Stadium.

For place-based policy, we consider trips related to Medical City Arlington, which is an important health care facility (Figure 2.10). Can travel to the hospital be covered by health insurance if it is included in the visit? The prediction results show that a 100% discount on weekdays could increase microtransit ridership to/from that location, from 42 to 140 trips/day, but it would require a subsidy of $544 per day ($141,440 per year). This policy provides a way for disadvantaged populations to have equitable access to healthcare.



	MT_ridership	revenue_fare	revenue_diff	trip_cv	P_microtransit	P_driving
100%_discount	140.0	0.000000	544.000843	167.517975	0.022355	0.514839
50%_discount	65.0	127.313847	127.313847	41.839233	0.010418	0.525700
No_discount	42.0	166.422913	0.000000	0.000000	0.006736	0.529138

Figure 2.10. Place-based subsidy policy for Medical City Arlington.

2.5 Discussion

This study presents a novel framework for forecasting and revenue management of microtransit services, using an agent-based, nested behavioral model. The framework addresses the unique challenges posed by the heterogeneous impacts of microtransit across different communities and the limited availability of detailed usage data.

Our AMXL model can effectively capture the heterogeneity in travel behavior and preferences, providing a robust tool for policymakers to simulate and evaluate various pricing and subsidy policies. The model's ability to integrate synthetic trip data and real-world usage data offers a comprehensive view of potential outcomes under different scenarios.

The case study, focusing on Via microtransit in Arlington, TX, demonstrates the practical application and effectiveness of this approach. Key findings from our study indicate that optimizing ride pass pricing can significantly enhance total revenue and consumer surplus. Specifically, reducing the weekly and monthly ride pass prices increased total daily revenue by $102 and total value by $363 per day. Additionally, the application of an event- or place-based subsidy policy showed potential in reducing car trips and increasing microtransit ridership, although these benefits require substantial subsidies. For example, a 100% fare discount at AT&T Stadium could reduce the number of car trips by 80 per day during peak hours but would require an annual subsidy of $32,068. A 100% fare discount at Medical City Arlington could bring 98 microtransit trips per day but would require an annual subsidy of $141,440.

Future work should focus on refining the model’s accuracy and expanding its applicability. This includes incorporating more microtransit data sources to better capture variations in user preferences and ground truth travel patterns. Additionally, exploring the impact of other factors, such as environmental benefits and equity impacts, can provide a more holistic view of microtransit's potential. Further studies could also extend this framework to other cities and other types of microtransit services such as fixed-route-deviated and/or zone-based, facilitating broader applicability and validation of the model.

3. Multimodal Trip-Chain Planner

3.1 Introduction

Trip chain decisions are influenced by the built environment, with workplaces often exerting a stronger influence on travel patterns than residential areas. Factors such as income and car ownership significantly impact these decisions, especially among low-income individuals and women, who may rely more on public transit for daily activities (Fields et al., 2022; Harris et al., 2011). Time of day and trip chaining behaviors also affect mode choices; while many travelers prefer their own vehicles for convenience, walking frequently serves as a complementary mode within multimodal trips, enhancing overall accessibility (Emily et al., 2019). Public transport usage varies across population groups, shaped by route availability, accessibility needs, and individual preferences (Yuan et al., 2023). Additionally, many commuters travel outside traditional peak hours, highlighting the demand for adaptable, on-demand transport solutions that better align with diverse schedules and support equitable access to essential services. This chapter reviews the existing features in trip planners (Section 3.2) and then presents a design for an open-source trip planner using Python libraries (Section 3.3). Finally, in Section 3.4, a feedback survey is conducted to evaluate preferences for 400 travelers in North Carolina.

3.2 Literature Review

Trip chain decisions are influenced by the built environment of various locations, especially primary activity destinations like workplaces, compared to residential areas. The non-linear relationships between built environment cases and trip chains should be considered for effective urban planning (Zhang et al., 2024). The influence of income and car ownership on trip chain decisions of low-income people, especially women, rely on public transit for their travel activities. High-income holders use public transit and active transportation in accessible areas, which shows that trip decisions are based on sociodemographic differences, accessibility, and affordability (Yousefzadeh-Barri et al., 2021). Travel mode choice is significantly influenced by time of day and trip chaining behavior. Individuals using owned vehicle, such as cars or bicycles, tend to stick to those modes throughout their trips. Walking often serves as a complementary mode in multimodal trip chains. Home and work locations can be used to predict mode choices and inform travel demands. (Scheffer et al., 2021). Public transport usage can be estimated based on observed traffic flow data, particularly in small networks, though it faces limitations when applied to larger networks or when the initial demand estimate is significantly off from the true values (Bhouri et al., 2021). For round-trip carsharing systems, three usage patterns exist: short stay, less-activity, and multi-activity trip chains, with the less-activity pattern being the most prevalent and associated with commuting (Feng et al., 2020). These usage patterns are commonly explained using behavioral models. In the recent years, shifting from aggregate behavioral models to individual behavioral models has shown to improve path choice predictions by capturing user-specific parameters and personal preferences, which are crucial for optimizing route planning and enhancing user satisfaction (Nuzzolo et al., 2015). Price incentives attract more users in ridesharing systems, particularly for longer trips, and that vehicle pick-up and return peak during specific hours, which can help optimize shared rides (Feng et al., 2020). Similarly, by optimizing time windows and service times, the shared-taxi service for disabled individuals can significantly reduce vehicle numbers and improve shared-ride efficiency. For example, a 20-minute time window reduced the fleet size by 30%, demonstrating the importance of balancing operational constraints with service quality (Recio et al., 2021). While two-way carsharing is more profitable due to longer rental times and distances, one-way carsharing integrates better with multimodal transport patterns, offering greater flexibility for users. Both systems are accepted equally by different income classes, but one-way services generate lower revenue per trip (Giorgione et al., 2021).

Finally, in terms of combining different modes, improving the intermodality between buses and bike-sharing could be as effective as enhancing the intermodality with subways. However, the results suggest that strategies for improving intermodality are not transferable across different transit modes (Kapuku et al., 2024). Commuters display higher travel frequency and more consistent spatial-temporal patterns than non-commuters, and a significant portion of commuters (73.98%) deviate from traditional peak commuting hours, highlighting the need for more flexible transportation services (Shi et al., 2024).

Comparative review of existing trip planners

Trip planners encompass a broad range of features ranging from comprehensive global trip planning (such as with Rome2Rio) to the real-time public transit or other mode information. Multimodal integration is relatively less common; however, is increasingly being offered across some platforms (such as City Mapper and Open Trip Planner). Each planner offers unique personalization features, allowing users to tailor their itineraries according to preferences. Some planner functionalities are commercially oriented (with paid subscription usage), while others incorporate open-source elements. Table 3.1 below presents an overview of trip planners and availability of features for multimodal integration, trip chain planning, real-time pricing, and open-source code.

Planner Name	Multimodal or not (to what extent)	Trip chaining feature?	Real-time pricing? Are detailed routes shown?	Open source? # of users	Reference link/citation
Rome2rio	Multi-modal route options: flights, trains, buses, ferries	Provides information on connecting routes but may not have a dedicated trip chaining feature	Prices are more generalized and may not always be the most accurate. Provides detailed information on routes and transportation options.	Partial code for the phone app is available: https://github.com/rome2rio/ Otherwise, it is not open source. It also doesn't publicly disclose user numbers.	https://thriftytraveler.com/guides/rome2rio-plane-train-or-automobile/
Moovit	Multimodal transit app, providing information on buses, trains, subways, and other transportation modes.	Supports trip planning with multiple modes of transportation. The app recently released real-time crowding and wheelchair accessibility features.	May not provide real-time pricing information. Provides detailed information on transit routes.	Not open source. Over 1.5 billion users across 112 countries worldwide before being acquired by Intel.	https://www.dailytarheel.com/article/2022/11/city-moov-it-app-cht https://www.masstransitmag.com/technology/passenger-info/mobile-applications/article/21210573/moovit-releases-realtime-crowding-wheelchair-accessible-feature-for-its-app
Citymapper	Multimodal transit app	Walking, cycling and driving, in addition to public transport.	No real-time pricing information.	Not open source.	https://www.pilotplans.com/blog/citymapper-review
Boston trip planner	Various transportation modes in the Boston area.	Supports planning local trips with different modes of transportation.	Real-time pricing may not be applicable, especially for public transit. Provides detailed information	Not open source.	https://www.mbta.com/trip-planner
GoTriangle	Provides information on buses and other local transportation modes.	Supports planning local trips with buses and other transit options.	No real time pricing. Provides detailed information on local transit routes.	Not open source.	https://gotriangle.org/
Google Maps	Highly multimodal platform, offering information on various modes.	Supports trip chaining with multiple modes of transportation.	Provides detailed information on transit routes, driving directions, and more.	Not open source. Has billions of active users.	https://www.google.com/maps
OpenTripPlanner (OTP)	Designed for multimodal trip planning.	Supports trip chaining and planning with various transportation modes.	Real-time pricing may depend on the data sources integrated with the specific deployment. Provides detailed information on multimodal routes.	Has an open-source platform. OTP relies on General Transit Feed Specification (GTFS) data to describe public transportation schedules and routes.	https://wiki.openstreetmap.org/wiki/OpenTripPlanner https://www.transitwiki.org/TransitWiki/index.php/OpenTripPlanner
Eurail and Interrail Pass Planner	Focused on train travel for Eurail and Interrail pass holders.	Plan train journeys for pass holders.	Real-time pricing not applicable, more about pass-based train travel. Provides detailed information on train routes for pass holders.	Not open source.	https://www.seat61.com/how-to-use-a-eurail-pass.htm
KAYAK	Travel search engine that includes flights, hotels, and car rentals.	Planning trips with flights, hotels, and car rentals.	Provides real-time pricing for flights, hotels, and car rentals. Detailed information on flights, hotels, and car rentals	Not open source.	https://www.kayak.com/

Trainline	Train travel but may include information on buses and other modes in some regions.	Supports planning train journeys.	Real-time pricing for train journeys. Detailed information on train routes.	Sells tickets on behalf of more than 140 rail and coach companies. Offers customers travel options across 36 countries. Not open source.	https://www.thetrainline.com/en-us
Loco2/Rail Europe	Train travel and rail transportation.	Supports planning train journeys.	Provides real-time pricing for train journeys. Detailed information on train routes.	Not open source.	https://www.seat61.com/websites/who-are-raileurope.htm
Omio (previously known as GoEuro)	Multimodal travel platform for trains, buses, and flights.	Supports trip planning with different modes of transportation.	Provides real-time pricing information. Provides detailed information on available routes.	Not open source.	https://www.omio.com/
Komoot	Primarily focused on outdoor activities and provides information on cycling and hiking routes.	Supports planning routes for outdoor activities	Provides detailed routes for cycling and hiking.	Not open source.	https://www.komoot.com/
HERE WeGo	Supports multiple transportation modes.	Supports planning trips with different modes of transportation.	May provide real-time pricing for some transportation options.	Not open source.	https://gisgeography.com/here-wego-maps/ https://www.onetripatatime.com/how-to-use-here-wego-for-easy-navigation-on-your-next-trip/

Table 3.1 Comparative review of existing trip planners

3.3 Trip Planner Design and Methodology

Research Design

This study focuses on creating an interactive trip-planning application that helps users plan journeys using different transportation modes and preferences. The application's goal is to allow users not only to input their starting point and destination but being able to choose multiple destinations, choose their preferred modes of transport, and receive optimized routes based on factors like travel time, number of transfers, and physical effort where applicable.

Data Sources

We used several data sources to build the application:

1. **OpenStreetMap (OSM) Data**: We downloaded map data from OpenStreetMap in the form of a .osm.pbf file. Durham was used as a case study because public transit is available there (the

model can be extended for any other location as well). This data provides detailed information about roads, paths, and other navigable routes necessary for planning trips.

2. **General Transit Feed Specification (GTFS) Data**: We downloaded the GoDurham GTFS data corresponding to the public transit information that includes bus routes, schedules, and stops.

3. **Digital Elevation Model (DEM) Data**: Elevation data was obtained from a DEM file from USGS website in a ".tif" format. The elevation data covering Durham city was downloaded and allows the application to calculate elevation changes and slopes along walking and biking routes.

Software and Tools

The application was developed using Python and several libraries and tools:

1. **Dash and Plotly**: Used for building the web interface and creating interactive maps and visualizations.
2. **r5py**: A Python library that wraps the R5 routing engine, used for calculating routes and travel itineraries based on various transportation modes.
3. **GeoPandas and Shapely**: Libraries for handling and manipulating geographic data and geometric shapes.
4. **Rasterio**: Used for reading and processing DEM files to extract elevation data at specific geographic coordinates.
5. **NumPy**: A library for numerical computations and handling arrays of data.
6. **Datetime**: Used for managing dates and times, especially for handling user-specified departure times.

Application Development

The application consists of several components:

1. **User Interface (UI)**: The UI was built using Dash components, providing input fields for users to enter their origin and destination coordinates. Users can also click on an interactive map to select these points. The UI allows adding multiple destinations to create a trip chain with several stops.

2. **Interactive Map**: Implemented using Plotly's Scattermapbox, the map enables users to interactively select locations and visualize their routes. It displays markers for the origin, destination, and any additional stops, as well as the calculated routes.

3. **Transportation Modes Selection**: Users can choose from various transportation modes, including walking, biking, driving, public transit, and shared rides. The application allows selecting the same mode for the entire trip or different modes for each segment between stops. Below are figures from the trip planner app interface.

4. **Departure Time Options**: Users can choose to depart immediately or select a specific date and time in the future. This feature helps calculate routes based on real-time or scheduled data.

5. **Optimization Criteria**: The application lets users optimize their trip based on different criteria. This applies to transit alone:

    1. **Total Travel Time**: Minimizes the overall time taken for the trip.
    2. **Number of Transfers**: Reduces the number of transfers between different transit services.
    3. **Wait Time**: Minimizes the waiting time at stops or transfers.
    4. **Walking/Biking Distance**: Reduces the distance that requires walking or biking.

These combined features are shown in Figures 3.1 and 3.2.

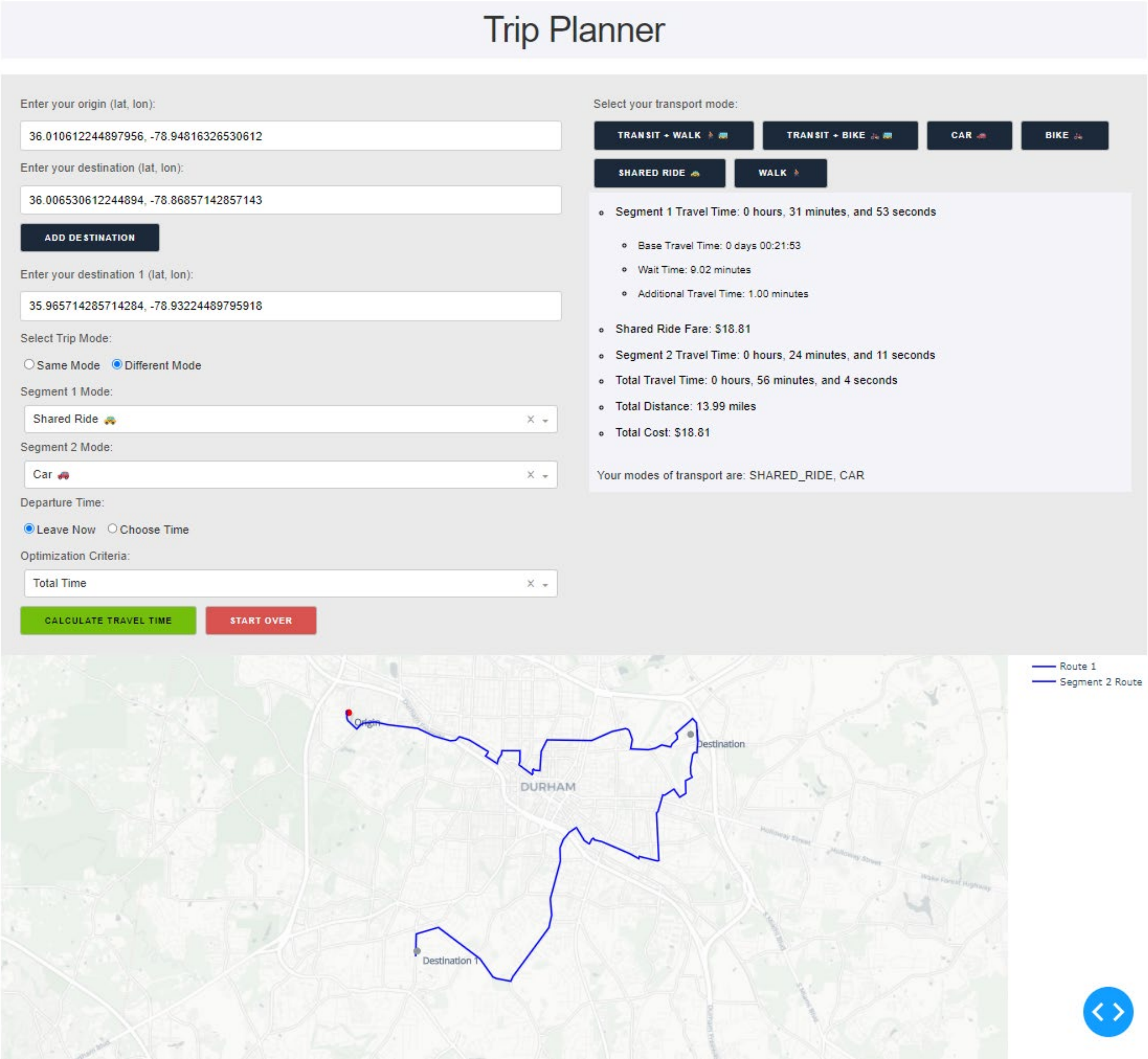


Figure 3.1: Trip Chaining Feature

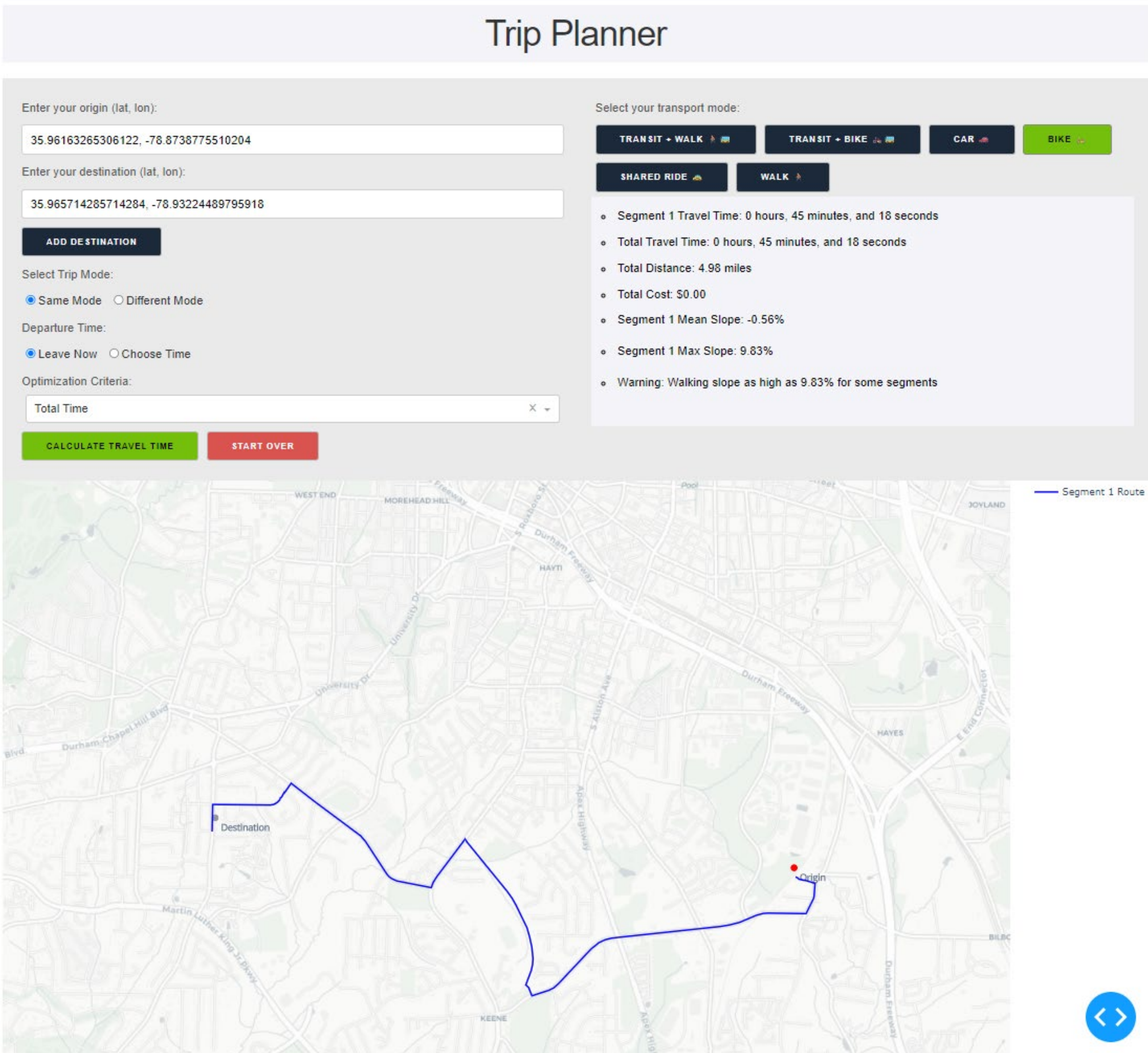


Figure 3.2: Slope Details for Biking Trips

Routing and Optimization Procedures

The application calculates routes using the following procedures:

1. **Route Calculation**: We used r5py package (Countinho et al., 2022) to compute routes between the specified origin and destination points. The routing engine takes into account the selected transportation modes, departure times, and optimization criteria for transit mode alone to generate the best possible routes. R5py is a Python library designed for efficient and realistic routing across multimodal transport networks, including walking, biking, public transit, and car travel. It offers an accessible and straightforward interface to R^5, which stands for Rapid Realistic

Routing on Real-world and Reimagined networks. For private modes of transport, it returns an option optimized by minimizing travel time. However, public transit routes return multiple outputs based on considerations like the number of transfers, shortest total time, and earliest arrival time.

2. **Transportation Modes Configuration**:

    1. **Walking, Biking and Driving**: Routes are calculated using algorithms based on Dijkstra’s or A* for routing that requires navigation over road networks.

    2. **Public Transit**: R5py uses MC-Raptor algorithm (Dibbelt et al., 2013) which incorporates bus and train schedules and routes from the GTFS data to provide accurate transit options. This can be optimized based on the output and user’s preference like returning the shortest route.

    3. **Shared Rides**: Utilizes road networks suitable for car travel but also can incorporate GTFS Flex data to use the information to more accurately provide itineraries based on additional requirements like limited pick up or drop off zones.

3. **Itinerary Computation**:

    1. For each trip segment (between two points), the application computes detailed itineraries that include travel times, distances, and any transfers needed and the planner displays these details based on the mode chosen.

    2. If trip chaining is being done (i.e., trips contain more than one segment or we have more than one destination), there is an option to select “Same Mode” if all segments share a single mode, else "Different Mode" is selected and the application computes routes separately for each segment based on the user-specified mode for that segment.

Elevations and Slope Analysis

To enhance the accuracy and usefulness of walking and biking routes, we included elevation and slope analysis:

1. **Elevation Data Extraction**: Using rasterio, we read the DEM file to obtain elevation values at specific geographic coordinates along the planned route.

2. **Slope Calculation**: We calculated the slope between consecutive points on the route using the Euclidean distance approximation formula:

- Elevation corresponding to the coordinate at the nodes along the route is obtained from the DEM file and the difference is calculated.
- Horizontal Distance is obtained using the Euclidean distance (which is a reasonable approximation for two points on a link segment) and multiplied by a constant to convert the degrees of latitude and longitude to distance.
- The slope is then the ratio of the change in the elevation to the horizontal distance.

3. **Slope Summarization**: For each route segment, we calculated the mean and maximum slope values. These values help assess the difficulty of the terrain, which is especially important for walking and biking routes.

4. **User Notifications**: If the maximum slope in a walking or biking segment exceeds a comfortable threshold (which we set at 7%), the application displays a warning message. This feature informs users about potential steep inclines that may affect their journey.

Cost Estimation

The application also provides cost estimates for different transportation modes:

1. **Public Transit Fare**: A fixed fare per ride (e.g., $1.00) is applied for each transit segment or based on the fare rules of the city. The fare amount can be generalized for other locations as well. The total transit cost is calculated by multiplying the fare by the number of transit segments used (i.e for all buses they take during transfer).

2. **Shared Ride Cost**: Costs are calculated using a fare model inspired by Uber's algorithm which includes:

   - **Base Fare**: A fixed starting charge.
   - **Cost Per Mile**: Charges based on the distance traveled.
   - **Cost Per Minute**: Charges based on the time taken.
   - **Service Fee**: Additional fees that may apply.

The formula used is: base_fare + (cost_per_mile * distance) + (cost_per_minute * duration) + service_fee + additional_fees. Distance is calculated in miles, and duration is in minutes.

3. **Total Trip Cost**: The application sums up the costs for each segment to provide an overall cost estimate for the entire trip. Walking, biking and driving segments are considered to have no monetary cost.

The designed app was hosted on Github platform and is publicly available on the Github page https://github.com/tml-ncat/Multimodal-Trip-Planner. Being designed as a Dash app, it requires a local instance run. Our future work aims to host it on web servers offered by services like Heroku.

3.4 Survey Analysis and Discussion

This section provides insights into the survey data collected to assess user preferences and requirements for the interactive trip planning application. By analyzing responses related to key features of trip planning, such as trip chaining, optimization criteria, and transportation mode preferences, we aimed to obtain a deeper understanding of the potential user base and their expectations. Appendix A includes the survey as launched. The findings from the survey will inform future iterations of the application's development.

Survey Objectives

The objectives of the survey are:

- To gather feedback on the capabilities of the trip-chain planner and understand user preferences on the interface.
- To assess the importance of different optimization criteria.
- To understand user behavior and preferences using sustainable modes of transportation.

The study primarily focused on residents of North Carolina to minimize variance from covering a larger geographical area. Respondents were categorized into **urban** and **rural/suburban** groups to better understand preferences based on the infrastructural differences influencing their choices. Urban counties included Wake, Mecklenburg, Durham, Guilford, Forsyth, Cumberland, Buncombe, and New Hanover, while all other counties were classified as rural/suburban. Data collection was conducted in two phases: a **pilot survey** on September 16, 2024, followed by the **final survey** from September 17 to September 23, 2024. The final survey incorporated additional questions based on feedback from the pilot. A total of **711 responses** were collected, with **406 fully completed**. After data cleaning, **359 responses** were used for analysis, consisting of **192 from urban areas** and **167 from rural/suburban areas**. Data collection was outsourced to **Dynata** to ensure prompt response times.

Summary of Key Findings

This section will highlight the results of the survey, focusing on the most important responses. Ranking scores were calculated by assigning values to respondents' selection for the preferences. **Do not prefer :0, Prefer slightly:1, Prefer a moderate amount:2, Prefer a lot:3, Prefer a great deal:4.**

Trip Chaining Preferences

- **Preference for Adding Multiple Destinations**: **40% of respondents** expressed a high preference (either "Prefer a lot" or "Prefer a great deal") for the ability to add multiple destinations when planning trips. This highlights the demand for flexible trip chaining in transportation apps. About **15%** do not prefer it at all.

- **Preference for Selecting Different Modes**: Similarly, **41% of respondents** preferred selecting different modes for different segments of their trip, indicating the importance of multimodal trip options. However, only **12%** do not prefer it at all.

Figure 3.3: Trip Chaining Results

Optimization Criteria for Route Planning

Respondents were asked to rank their preferences for various optimization criteria when selecting travel routes. When planning trips, 66% of respondents prioritized minimizing costs, making it the top concern, while 60% preferred routes with fewer tolls. Efficiency was also key: 48% wanted to minimize walking time, 53% valued fewer transfers, and 50% preferred shorter walking or biking distances. These findings highlight the need for affordable and efficient travel options. Urban area residents particularly had more interest in public transit related information like minimizing walking time and distance, number of transfers. This could be due to public transit common in those areas.

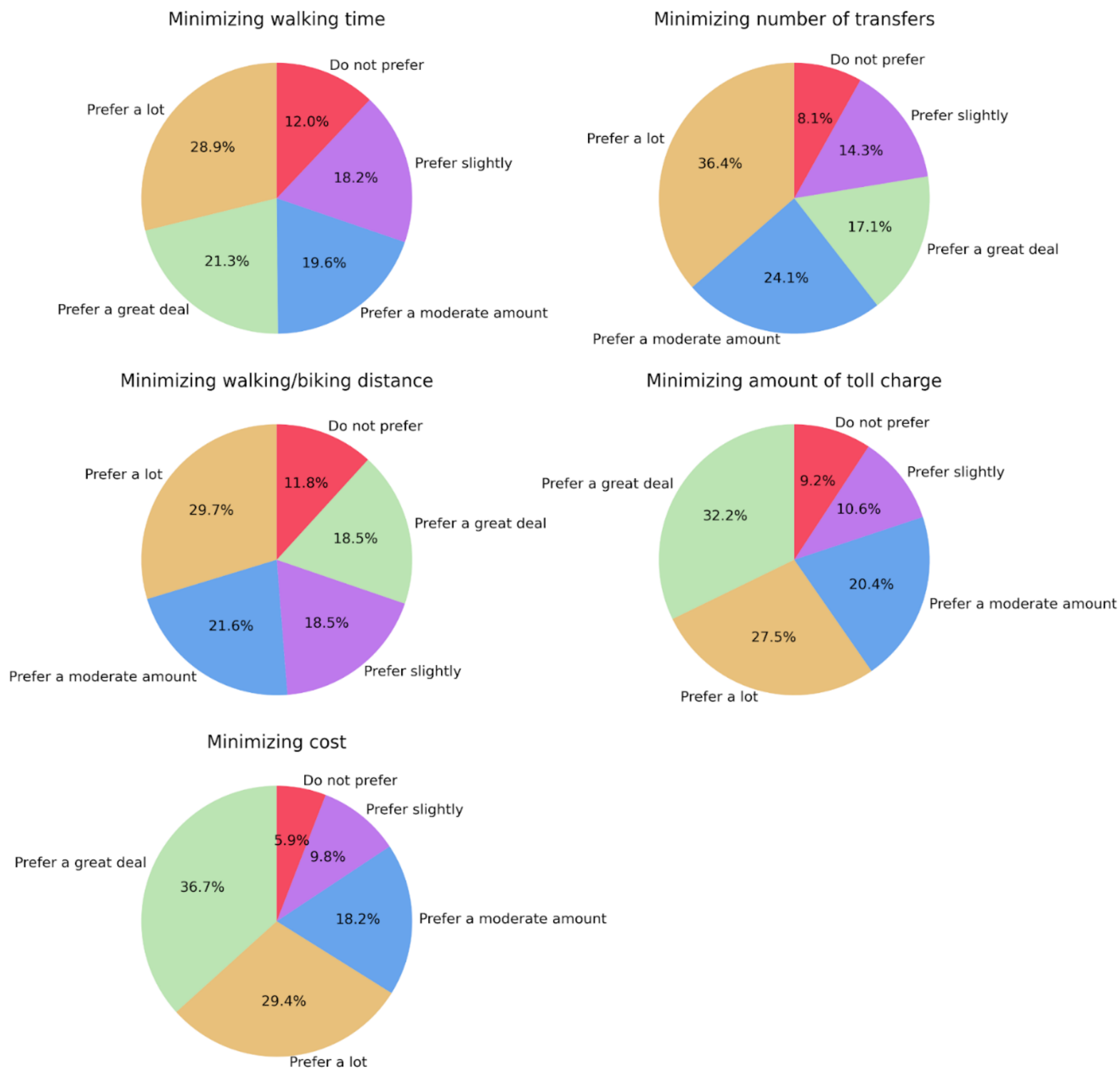


Figure 3.4: Optimization Preference

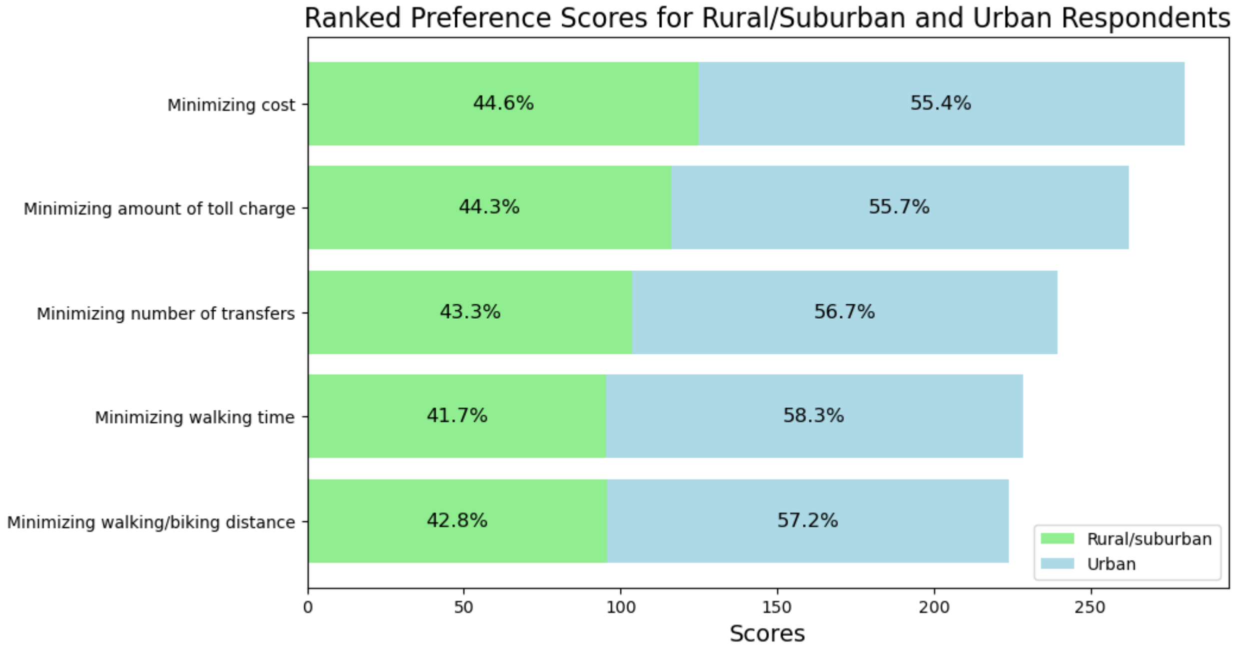


Figure 3.5: Optimization Ranking (the total scores are shown on the x-axis and the breakdown of rural vs urban amongst the total is shown using varying colors)

Detailed Statistics Preference

Similarly, respondents were asked to rank their preferences for various information related to motorized vehicles. A significant 60% of respondents preferred to see discount information on their trip planning apps, while only 11% were not interested. Similarly, 56% valued congestion updates, with the same percentage opting out. However, only 31% wanted carbon emissions data, and 26% preferred not to see it at all. Discounts ranked highest in preference, while carbon emissions ranked lowest. The lack of preference for the display of shared ride information was primarily from rural area residents; this suggests that shared rides are not popular or unavailable. Additionally, the majority of rural respondents did not care about carbon emission information being displayed on their trip planning app; this could be because they don't have many alternatives to driving and prefer not to be disturbed by the extra information.

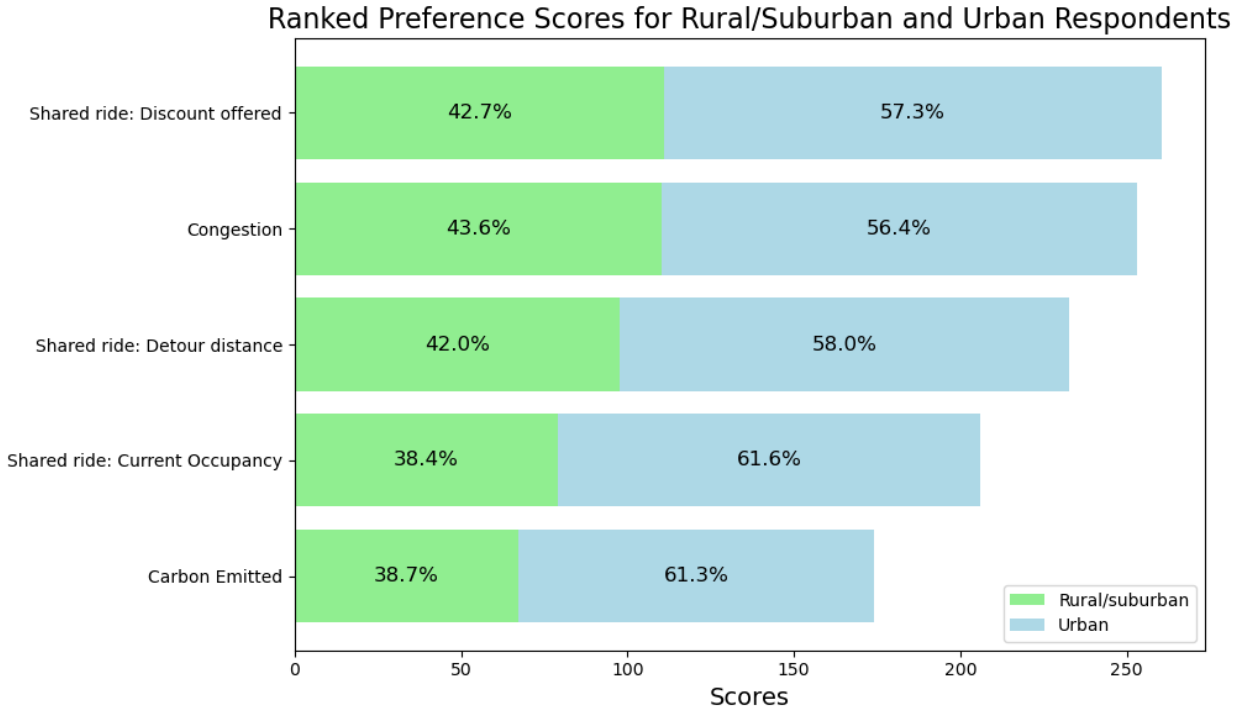


Figure 3.6: Motorized Statistics Ranking

Non-Motorized Transportation Statistics

The survey collected detailed responses on the use and perception of non-motorized transportation modes (walking and biking). Several key factors influence users' decisions to walk or bike. Road safety stood out as the top concern for 60% of respondents when considering walking or biking, with key worries focused on interactions with motor vehicles and the condition of pedestrian and bike paths. On the other hand, features like pollution and noise were less prioritized, with 22% showing no preference for these, although 34% still expressed strong interest in seeing this information in their trip planning. The majority of rural respondents did not care about the non-motorized information, except for road safety, which was split fairly evenly between urban and rural respondents. This could be because rural residents mostly rely on private vehicles and seldom bike or walk, as their destinations are widely dispersed compared to urban areas.

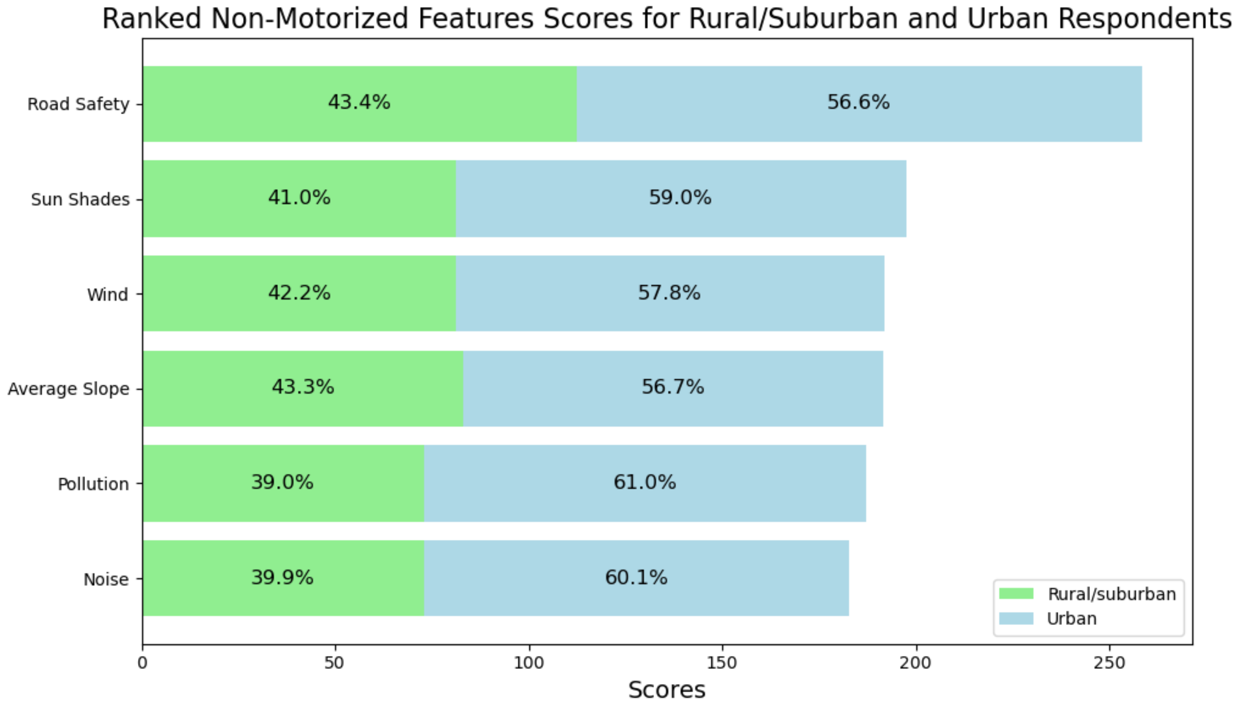


Figure 3.7: Non-Motor Statistics

Sustainability and Environmental Considerations

Respondents demonstrated varying levels of concern for environmental impact. Nearly half of the respondents (47%) showed a strong preference for receiving nudges to use sustainable modes like biking, especially if it helped them avoid traffic congestion and save time, while only 15% were not interested. When it comes to earning credits for sustainable transportation, 33% were not interested, though 30% favored receiving such incentives, indicating room for growth in incentivized schemes. Again, rural residents were less inclined to use sustainable modes of transportation, though some would consider using the modes if it reduced congestion for them. Rural residents were generally not interested, even if they could earn credits to rent e-scooters or other similar modes. Urban residents, on the other hand, made up the majority of the score for earning credits.

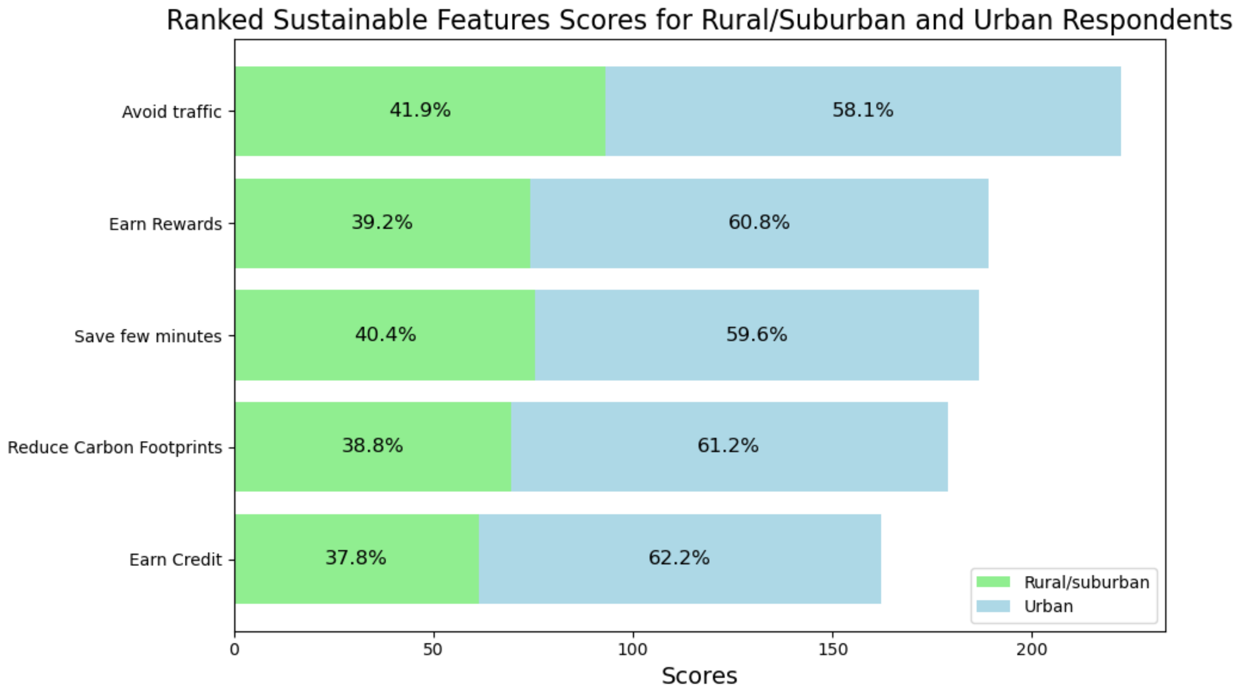


Figure 3.8: Sustainable Statistics Rankings

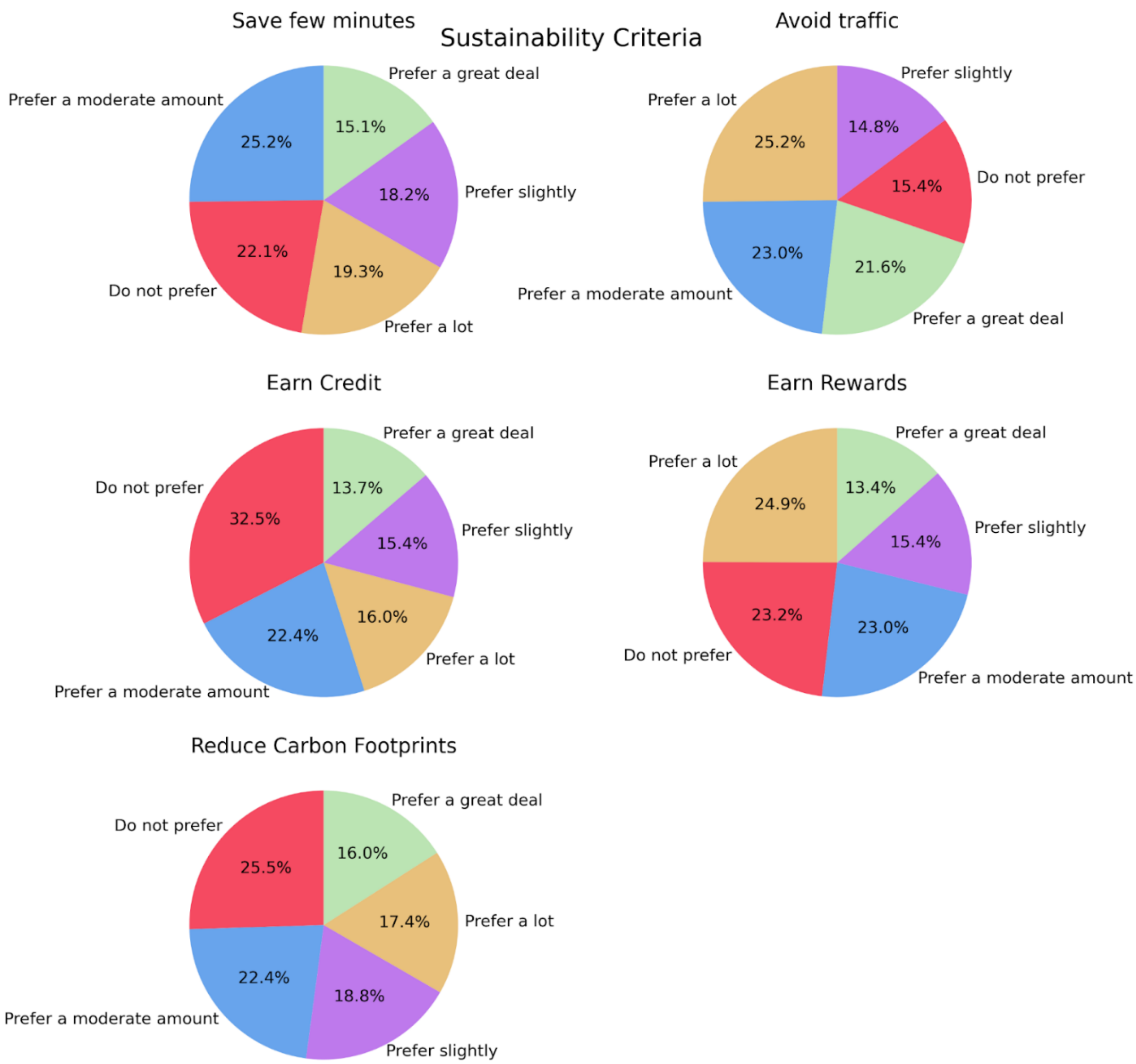


Figure 3.9: Sustainability Criteria

Barriers to Sustainable Transportation

When asked about barriers to using sustainable transportation modes, the following were the top factors. A lack of convenience was a key barrier for 24% of respondents, particularly due to infrastructure or schedule limitations. Additionally, 21% were discouraged from using sustainable modes because of longer travel times compared to driving. Personal comfort and safety concerns were also notable, with 16% each citing these factors as reasons for preferring personal vehicles, reflecting a desire for privacy and control. However, a higher percentage of rural respondents cited lack of reliable public transportation options as a top barrier to using sustainable transportation.

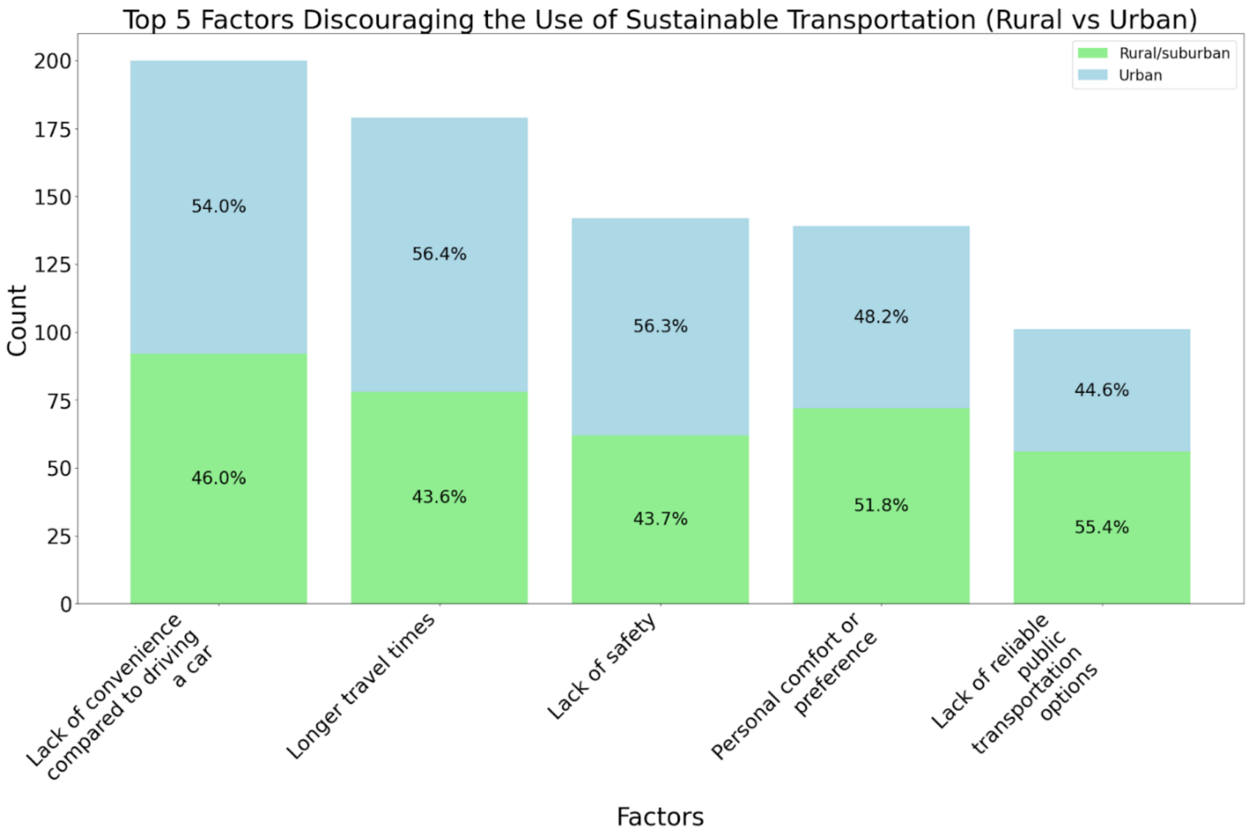


Figure 3.10: Barriers to Sustainable Transportation

Sustainability and Age Group

Younger adults (18-44) generally show strong support for sustainability, though some express concerns about its practicality. Middle-aged individuals (45-64) maintain a focus on sustainability, but their concerns about other factors, such as convenience and safety, grow. In contrast, older adults (65+) tend to prioritize other considerations over sustainability, indicating a shift away from it as a primary focus in their decision-making.

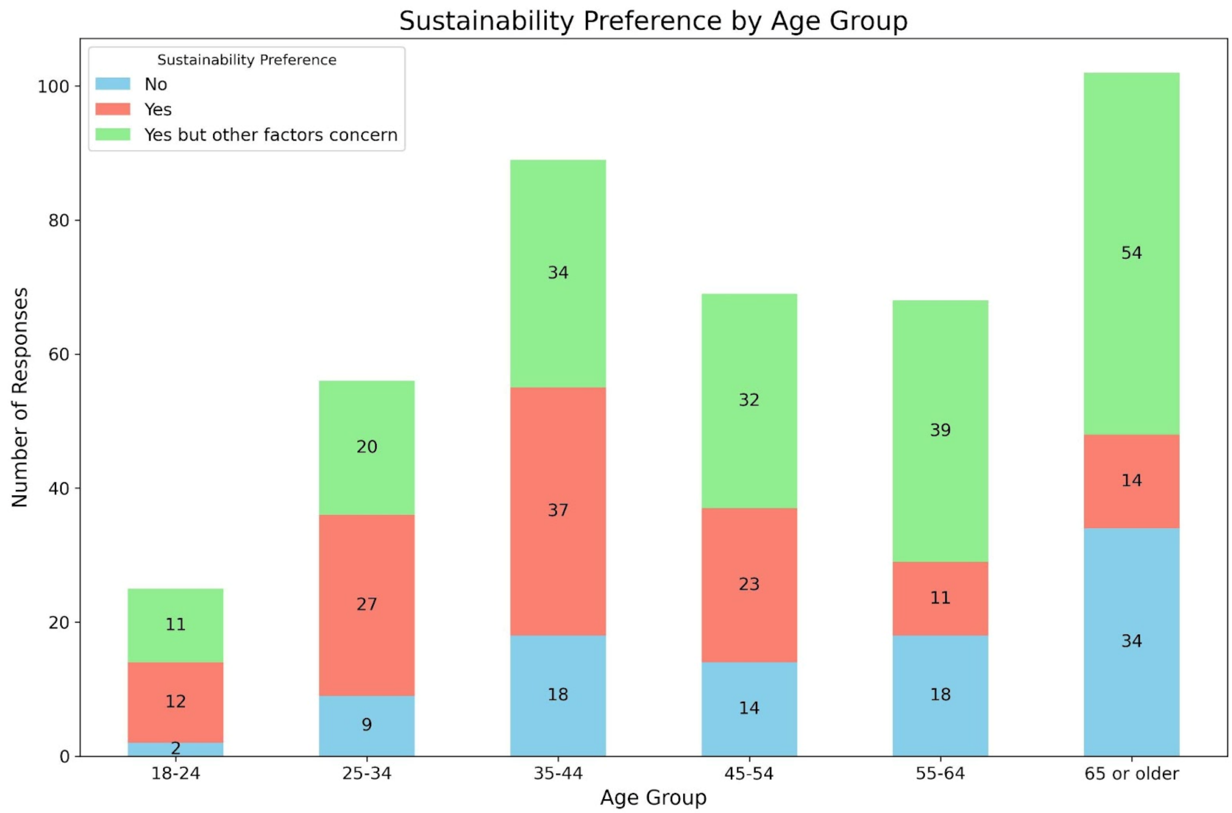


Figure 3.11: Sustainability Preference by Age Group

Preferred Mode of Transport

The survey results show a clear preference for different transportation modes, as demonstrated in figure 3.11. Private vehicles were the top choice for 70% of respondents, with 47% selecting them as their second preferred mode, primarily due to convenience, privacy, and comfort. Public transit, while less popular, was favored by 5% as their main mode of transport, especially in urban areas where it serves as a practical alternative to driving, with 8% choosing it as their second preferred mode. Biking saw lower adoption overall, but walking emerged as a popular second choice, making it the most attractive alternative after private cars for secondary preferences. While car ownership levels are similar in both rural and urban areas, the number of people without cars in urban areas is four times higher than in rural areas. This disparity can be attributed to the greater availability of alternative transportation options in urban settings, such as public transit and ride-hailing services, which are significantly more popular than in rural regions. The fact that no rural respondent selected walking as their first choice further highlights how dispersed settlements are in rural areas.

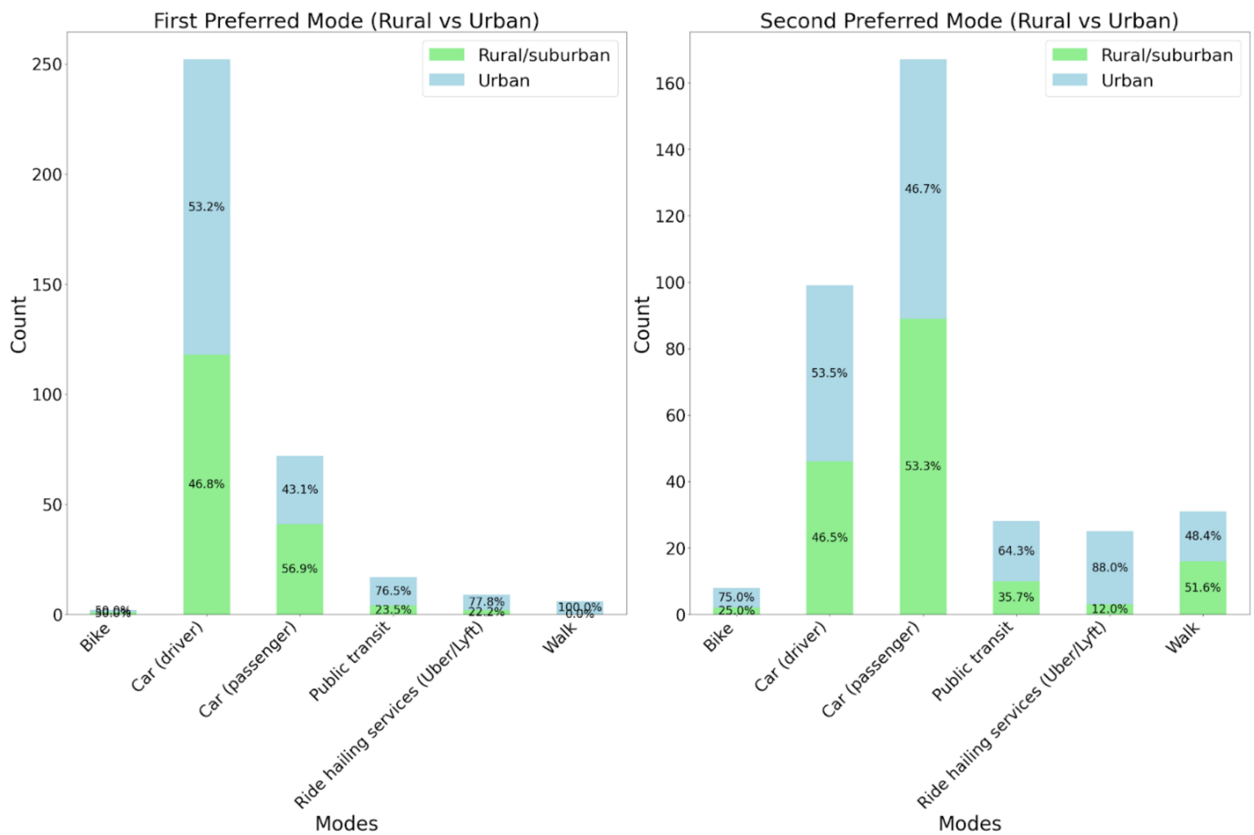


Figure 3.12: Mode Preference

Criteria for Choosing Route and Mode of Transport

When selecting a transportation mode, respondents ranked time and cost as their top priorities, with 24% choosing each as the most important factor. Convenience followed closely, with 20% of respondents emphasizing its importance. Road safety was also a significant concern for 16% of respondents, influencing their decisions to avoid biking or walking when infrastructure lacked protection from motor vehicles.

When choosing a transportation route, 22% of respondents prioritized travel time, while 19% considered distance to be the key factor. Both cost and traffic congestion were important for 15% of respondents, highlighting their concern for affordability and smoother travel. Rural and urban respondents had similar criteria for choosing both modes and routes of transportation. However, respondents from urban areas cared more about environmental impacts than those in rural areas.

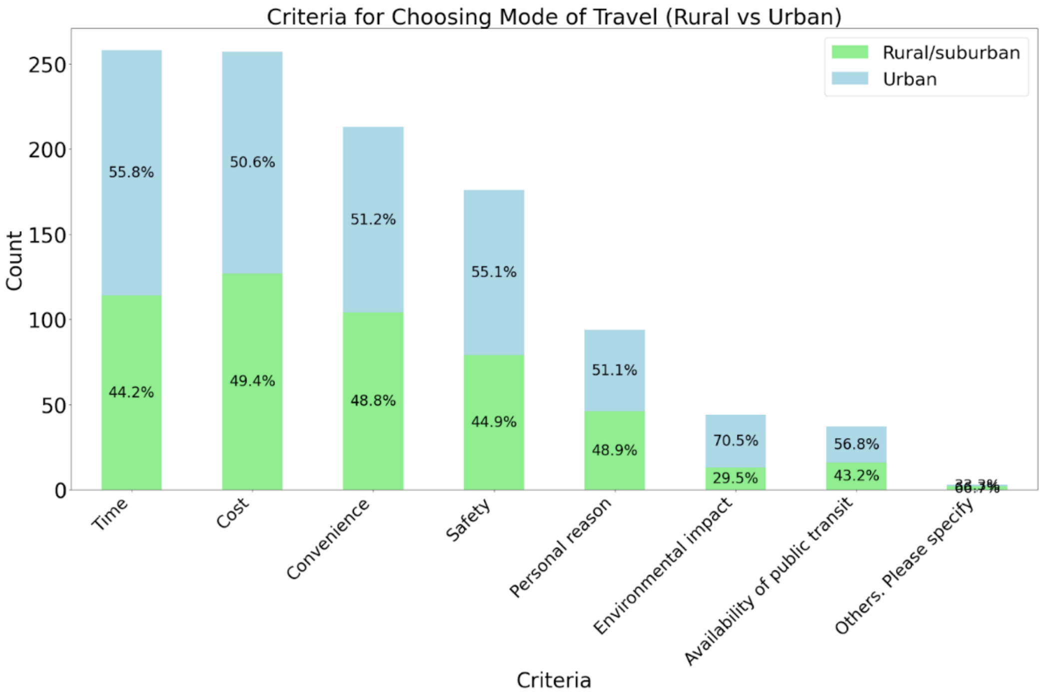


Figure 3.13: Mode Choice Criteria

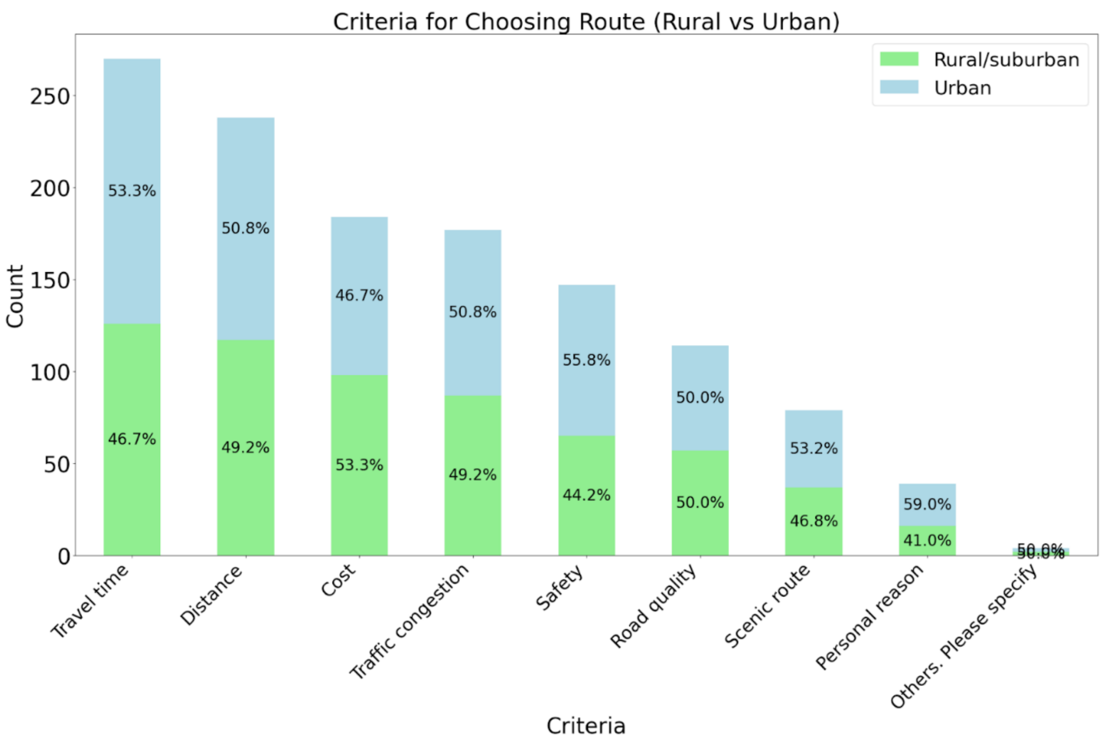


Figure 3.14: Route Choice Criteria

Infrastructure and Cost-Related Barriers

The survey highlighted significant barriers related to infrastructure and costs that deter people from using sustainable transport options like public transit, biking, or walking. The high upfront cost of purchasing an electric vehicle was the most significant cost-related barrier to adopting sustainable transport, with 26% of respondents citing it. Concerns about maintenance and repair costs followed closely, mentioned by 23% of participants. On the infrastructure side, the poor condition of sidewalks or walking paths was the top barrier, selected by 21% of respondents. Inadequate public transit coverage or connectivity was the second-highest infrastructure-related reason, with 19% of respondents citing it as a deterrent to using sustainable transportation modes.

Limited/Vulnerable Road Users

Respondents indicated that vulnerable or limited road users prioritize features that address real-time challenges and physical barriers, with a particular emphasis on rural travel needs. Offline functionality in poor network areas was the top priority, with 21.9% of users highlighting the importance of being able to access trip planning features in areas with limited connectivity. This underscores the need for reliable tools that work even without network access.

Real-time accessibility information for trip chains followed closely at 17.2%, reflecting the value users place on up-to-date data about the accessibility of each stage of their journey. Alternate modes of travel in rural areas, such as bikes or mobility aids, were also significant, with 11.2% of respondents ranking this feature as important. Lastly, planning features that allow for caretakers or companions to assist during travel were noted by 11.0% of users, showing that while less of a priority, it remains important for a portion of the population.

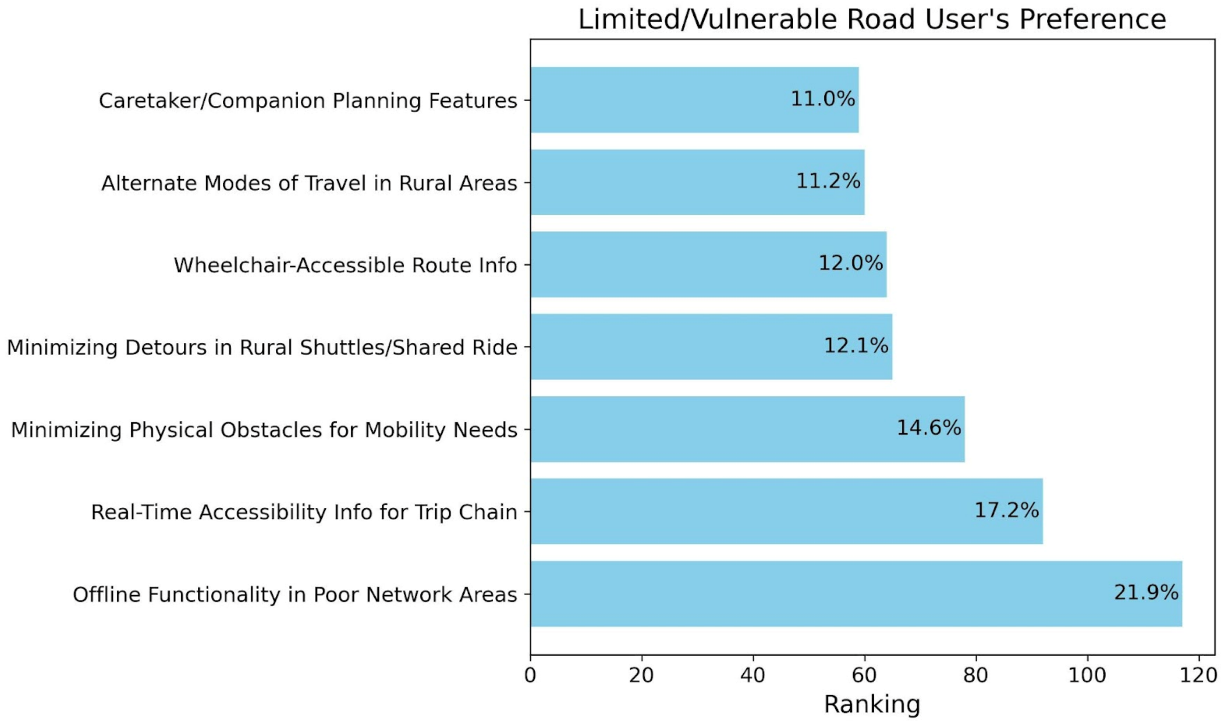


Figure 3.15: Limited/Vulnerable Road User's Preference

Demographics

In terms of **employment status**, the data reflects a population where a substantial portion of respondents are either working full-time (39.4%) or retired (30.8%), indicating a mix of active professionals and those no longer in the workforce.

For **gender**, the majority of respondents were female, comprising 60.6% of the population, compared to 39.4% male.

The **age distribution** reveals that the largest group of respondents are 65 or older, with a strong representation from middle-aged adults (35-44). Younger age groups (18-24 and 25-34) are less represented, suggesting that the data skews toward a more mature or elderly demographic.

In terms of **education**, most respondents have completed at least high school, with a significant portion having college experience or degrees. The largest group (23.7%) has some college education, followed by those with a 4-year degree or high school diploma (both at 22.2%). Additionally, 15.2% of respondents hold advanced degrees, indicating a well-educated sample, with very few lacking a high school diploma.

Both types of counties report exceptionally high rates of smartphone ownership to access trip planner apps, with over 90% of respondents in each category owning a smartphone. The number of respondents without a smartphone is minimal.

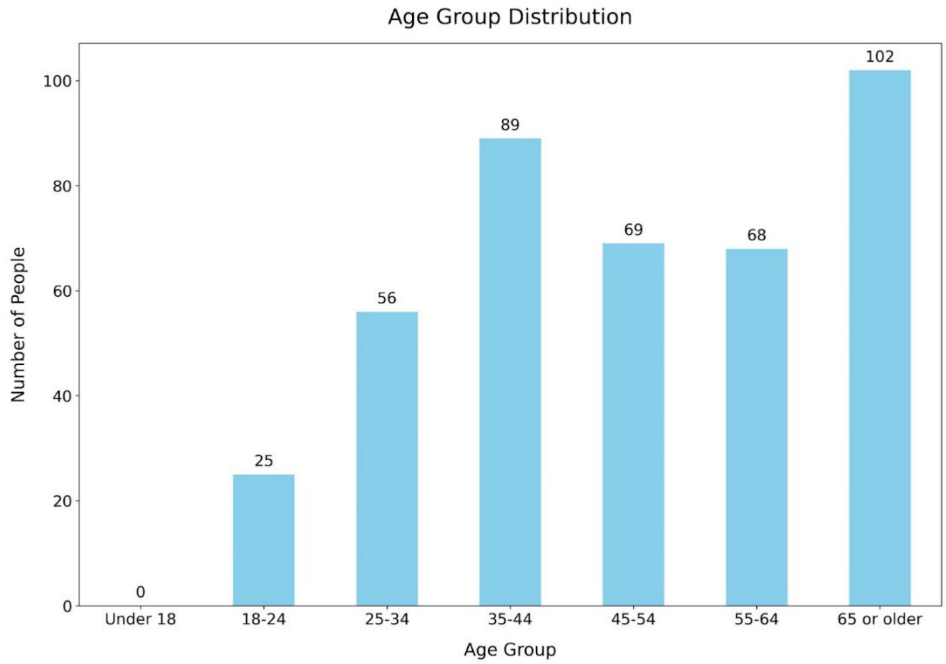


Figure 3.16: Age Group

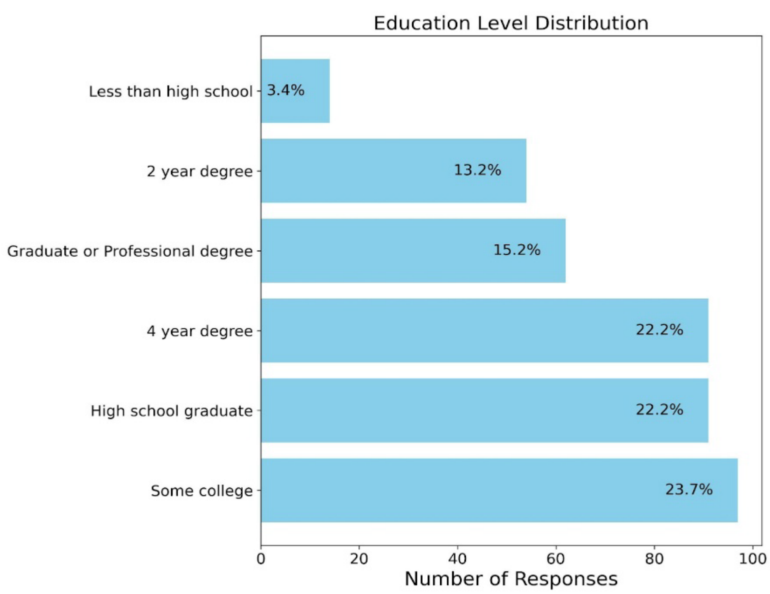


Figure 3.17: Education Level Distribution

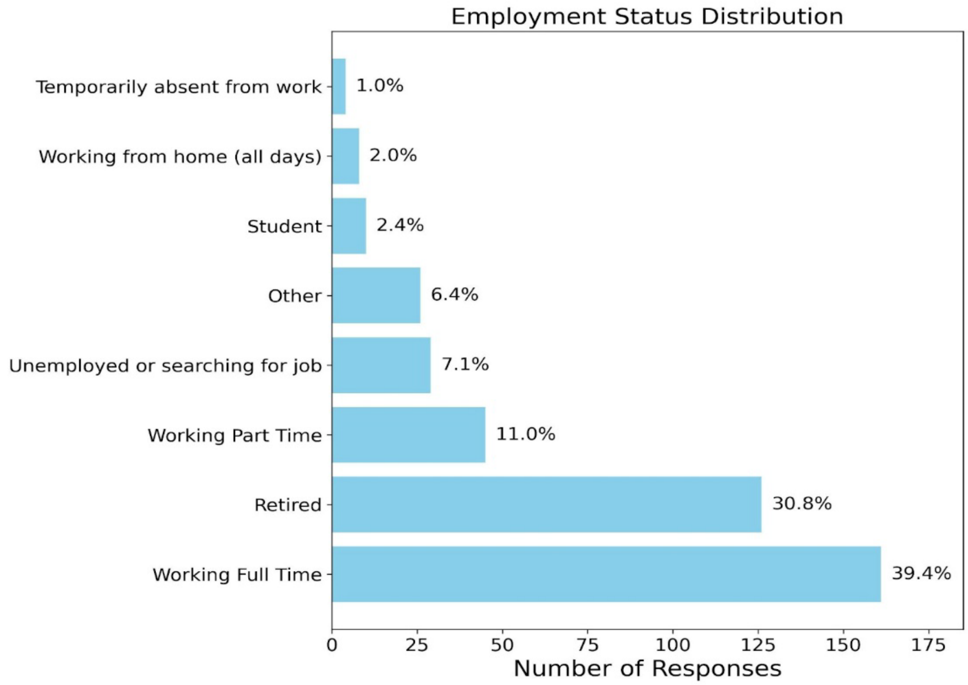


Figure 3.18: Employment Status Distribution

The pie chart shows respondents' preferences for the system-optimized departure time feature, where the app suggests the best time to leave. The majority, 29.7%, prefer this feature a lot, while 24.9% prefer it moderately. A notable 20.7% prefer it a great deal, with 16.2% slightly preferring it. Only 8.4% do not prefer it. Overall, most respondents view the feature positively.

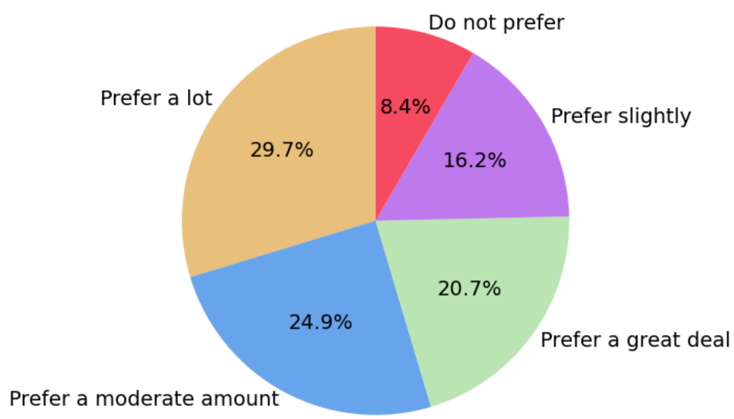


Figure 3.19: Optimized Departure Time

Discussion of Findings

- **Cost Elements:** Users are generally more receptive to information that is related to monetary elements such as tolls and discounts. Preference for this information is popular among respondents.
- **User-Centric Design:** Users generally prefer receiving extra information that would help in their trips such as avoiding congested areas, having an option for the app to suggest an optimized time, and other features like road safety. They don't find other information like carbon footprint, pollution, or noise appealing, as this doesn't directly aid their trips.
- **Sustainability Preference:** Prioritizing sustainability when choosing mode of transportation is more popular among young and middle-aged adults. However, other factors like convenience, cost, and time are distributed among all groups.

The survey's open-ended comments provided insights into participants' views on trip planner features. Older respondents expressed a lower preference for biking but were more open to walking if adequate sidewalk infrastructure was available. Many participants lacked awareness of trip planners and their benefits, with some older adults mentioning discomfort with using smart devices. Additionally, some respondents noted that certain trip planners do not cover intercity trips, limiting their usefulness for long-distance travel. There was also a strong emphasis on the need for trip planners to include information on amenities like gas stations, rest stops, charging stations, medical facilities, and emergency services. Lastly, concerns about weather conditions and the risk of contracting illnesses such as the flu or COVID-19 in public transportation were significant factors influencing travel choices.

3.5 Conclusion

The development of a multimodal trip-chain planner is a big step forward in helping travelers with limited mobility or other challenges. By including different types of transportation, live updates, and smart planning options, this tool can greatly improve access and convenience for people with limited mobility access. Additionally, the inclusion of advanced user behavior models ensures a seamless and user-friendly experience, while considering both sustainability and user constraints.

In the long term, this trip planner has the potential to transform how individuals plan their journeys across different transportation modes, fostering more inclusive, sustainable, and accessible travel for everyone.

4. Summary, Key Findings, and Lesson Learned

This project developed a multimodal trip-chain planner and a behavioral framework to address the diverse mobility needs of disadvantaged travelers, with a focus on both trip planning preferences and revenue management strategies. Through a combination of survey analysis, behavioral modeling, and a practical case study in Arlington, TX, the project highlights several key factors influencing transportation choices and the potential for policy interventions to improve access and mobility.

Survey Insights: The survey results underscore critical user priorities for trip planning features, with cost and time optimization emerging as the most valued criteria (66% of respondents). Road safety and convenience were also influential, especially among vulnerable groups who prioritize accessible and reliable options. While features like trip chaining and multi-modal support received strong support, practical implementation challenges persist, particularly in rural areas where infrastructure and connectivity limitations restrict sustainable transportation options. Enhancing infrastructure in these regions could reduce dependency on private vehicles and foster more sustainable travel behaviors. Respondents valued incentives like discounts and congestion information, although environmental data (e.g., carbon emissions) ranked lower, suggesting that sustainability remains a secondary consideration for many users, especially in rural settings.

Behavioral Model and Revenue Management Framework: The project introduced an agent-based, nested behavioral model (AMXL) to capture the heterogeneity of travel preferences and optimize microtransit revenue. This model enables policymakers to simulate various pricing and subsidy strategies, offering a nuanced approach to evaluating the impact of microtransit on diverse communities. The Arlington case study demonstrated that reducing ride pass prices led to notable gains, with total daily revenue increasing by $102 and consumer surplus by $363. Event- and place-based subsidies further increased microtransit use but required substantial financial support to be effective. For instance, a 100% fare subsidy at AT&T Stadium could cut 80 car trips per day during peak hours but would require an annual subsidy of $32,068.

Key Lessons and Future Directions: The trip planner and behavioral framework developed here not only align with USDOT's equitable mobility goals but also underscore the importance of considering localized needs in trip planning and microtransit adoption strategies. Future work should focus on refining the model's predictive accuracy, integrating broader datasets to capture variations in user preferences, and exploring the effects of factors like environmental impact and equity. Extending this framework to other cities and microtransit types, such as zone-based services, can provide further validation and applicability across diverse urban and rural contexts.

The survey results highlight several important factors influencing user preferences for trip planning features. **Cost and time optimization** were the top priorities, with 66% of respondents selecting these criteria for planning trips. Road safety and convenience also played a significant role in mode selection, especially among vulnerable users who prioritize features addressing physical and real-time challenges.

While the majority of users showed strong support for features like **trip chaining** (adding multiple destinations and selecting different modes), there were still concerns about practical implementation, particularly in rural areas where infrastructure and connectivity can limit sustainable transportation options. Enhancing infrastructure and connectivity in rural areas could be a crucial first step in encouraging residents to prioritize sustainability and reduce their dependence on private vehicles. Improved infrastructure would also make residents more open to adopting incentives aimed at shifting behavior toward more sustainable practices. **Discounts and congestion information** were highly valued, while **carbon emissions data** ranked lower, indicating that environmental considerations are not yet a major driver for the majority of users, especially in rural areas.

4.1 Limitations of the Study

Several limitations emerged in this work. First, the demographics skewed toward older and retired individuals and may not fully reflect the preferences of younger populations, who are likely to have different mobility needs and technology usage habits. Additionally, while rural respondents were represented in the survey, some questions—particularly those related to sustainable transportation modes—were less popular among this group. This limits our ability to draw firm conclusions based solely on geography. The responses suggest that rural residents may face different challenges and priorities compared to their urban and suburban counterparts, making it difficult to generalize preferences across regions without further study.

4.2 Future Work Directions

In the future, addressing these limitations could involve expanding the survey to include a more diverse age group and targeting rural areas where **public transit and sustainable modes** may be less available but could provide important solutions. Further development of the trip planner should explore **personalized mobility solutions**, such as providing tailored recommendations based on individual user behavior and preferences, including **earning credits for sustainable transportation**. Expanding on the **incentivization** model, the potential for **gamification** of sustainable travel, where users earn rewards or credits for adopting greener modes, can be explored. Additionally, integrating **offline functionality** and real-time updates can address the barriers related to **poor connectivity** in rural areas.

4.3 Policy Recommendations

Based on the findings, several policy recommendations emerge:

1. **Encourage Multi-Modal Integration**: Policymakers should support the integration of various transportation modes, especially in **trip chaining**, by improving infrastructure for walking, biking, and public transit connections, particularly in suburban and rural areas.

2. **Incentivize Sustainable Transportation**: Governments should develop **incentive programs** for using sustainable modes, such as providing credits for biking, walking, or using public transit. These credits could be redeemed for rewards or discounts on transportation services, similar to the systems some cities have piloted.

3. **Improve Infrastructure in Rural Areas**: Investment in **rural public transit infrastructure** and **safe pedestrian pathways** can reduce barriers to adopting sustainable modes, addressing concerns about safety and accessibility that were prevalent in the survey responses.

4. **Support for Vulnerable Populations**: Policies should prioritize **user-centered designs** that accommodate the needs of vulnerable populations, including those with limited mobility. This includes ensuring **accessibility features** like wheelchair accessible routes and other functionalities tailored to their needs.

By addressing these key areas, future work can build a more inclusive, efficient, and sustainable trip planning system that aligns with the evolving needs of all users, especially in regions with limited access to transportation options.

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Appendix

Link to the survey as launched: Trip Planner Survey.pdf