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A nested nonparametric logit model for microtransit revenue management supplemented with citywide synthetic data

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Abstract

As an IT-enabled multi-passenger mobility service, microtransit can improve accessibility, reduce congestion, and enhance flexibility. However, its heterogeneous impacts across travelers necessitate better tools for microtransit forecasting and revenue management, especially when actual usage data are limited. We propose a nested nonparametric model for joint travel mode and ride pass subscription choice, estimated using marginal subscription data and synthetic populations. The model improves microtransit choice modeling by (1) leveraging citywide synthetic data for greater spatiotemporal granularity, (2) employing an agent-based estimation approach to capture heterogeneous user preferences, and (3) integrating mode choice parameters into subscription choice modeling. We apply our methodology to a case study in Arlington, TX, using synthetic data from Replica Inc. and microtransit data from Via. Our model accurately predicts the number of subscribers in the upper branch and achieves a high McFadden R^2 in the lower branch (0.603 for weekday trips and 0.576 for weekend trips), while also retrieving interpretable elasticities and consumer surplus. We further integrate the model into a simulation-based framework for microtransit revenue management. For the ride pass pricing policy, our simulation results show that reducing the price of the weekly pass (\$25 \rightarrow \$18.9) and monthly pass (\$80 \rightarrow \$71.5) would surprisingly increase total revenue by \$127 per day. For the subsidy policy, our simulation results show that a 100% fare discount would reduce 61 car trips to AT&T Stadium for a game event, and increase 82 microtransit trips to Medical City Arlington, but require subsidies of \$533 per event and \$483 per day, respectively.

Keywords: nonparametric logit, mode choice, subscription choice, microtransit simulation, Arlington Via

1. Introduction

Microtransit, an emerging form of Demand Responsive Transit (DRT) service, bridges the gap between fixed-route transit and ride-hailing services by offering flexible, on-demand transportation in dynamically routed shuttles or vans (Slosky et al., 2022; Volinski et al., 2019). In this ridesharing system, adaptable routes and schedules enable multiple passengers to share a vehicle when their travel plans align closely in a spatiotemporal sense (Daganzo & Ouyang, 2019). Empirical studies have highlighted the potential of microtransit in enhancing mobility for underserved populations (Erdoğan et al., 2024), replacing fixed-route public transit in rural residential areas (Hansen et al., 2021), and relieving traffic congestion by reducing the usage of private vehicles (Kawaguchi et al., 2017). Despite these promising benefits, the financial viability of microtransit remains precarious. The reliance on public subsidies and short-term pilot funding necessitates intelligent, behaviorally-aware revenue management strategies to achieve long-term profitability (Ghimire et al., 2024).

Simulation-based frameworks are proven to be effective in evaluating complex mobility systems (Jung & Chow, 2019; Markov et al., 2021; Yoon et al., 2022). The dispatching operation of microtransit service involves optimizing vehicle routes and schedules for user-requested trips, making its simulation closely related to solving dynamic pickup and delivery problems (Ho et al., 2018; Ma et al., 2019). Recent advances in last-mile service optimization (Costa et al., 2021), non-myopic routing algorithms (Namdarpour et al., 2024), and “day-to-day” equilibrium models (Rath et al., 2023) have demonstrated the ability to forecast microtransit ridership and quantify profit potentials.

However, critical gaps persist in microtransit demand estimation: existing behavioral models for microtransit simulation remain oversimplified and constrained by three key limitations. First, the reliance on stated preference (SP) surveys with small sample sizes inadequately captures population-level user preference in real-choice situations, leading to less representative patterns of microtransit usage (Bills et al., 2022; Ren et al., 2024). Second, assumptions on the distribution of taste parameters may fail to capture heterogeneous user sensitivities to travel time, cost, and specific modes. Though mixed logit models (McFadden & Train, 2000) allow taste parameters to follow normal, uniform, or triangular distribution, the estimation of these parametric distributions could be biased when there are unobserved factors like environmental attitudes, social norms, or habitual behaviors (Hess, 2010; Sarrias, 2020). Third, existing models largely overlook subscription-based ride pass programs (e.g., weekly or monthly passes), which is a critical revenue stream and pricing structure for microtransit operators (Marino & Jayakrishnan, 2024). This oversight is primarily due to the lack of individual subscription data caused by privacy constraints. As a result, focusing solely on trip-level choices may weaken the link between subscription adoption, induced usage, and long-term profitability.

To address the gap, we propose a novel behavioral model estimated using a combination of synthetic population data and marginal subscription data. The model features a nested structure for joint travel mode/ride pass subscription choice and a nonparametric parameter distribution that best fits the large choice dataset. Our model is significant in three aspects: (1) restrictive SP survey data is replaced with synthetic population data, which reveals diverse, citywide travel patterns and improves the spatiotemporal granularity in microtransit choice modeling; (2) the lower-branch mode choice model employs an agent-based estimation approach (Ren & Chow, 2022), which captures travelers’ heterogeneous preferences for microtransit at the population level, individual

level, and trip level; and (3) parameters from the lower branch are integrated into the upper branch, making it possible to estimate a subscription choice model using marginal ride pass data.

We further integrate the behavioral model into a simulation-based framework for microtransit revenue management in which (1) an open-source microtransit simulator is calibrated to quantify waiting and in-vehicle time under fixed demand; (2) a dynamic adaptation loop is constructed to equilibrate supply-side service performance and demand-side behavioral feedback; and (3) performance metrics such as total revenue, total ridership, total consumer surplus are constructed for policy evaluation.

In a case study, we apply our methodology to Via Arlington, a microtransit service that serves as the only public transit option in Arlington, TX ([City of Arlington, 2024](#)). We estimate the behavioral model using synthetic population data from [Replica Inc.](#) and marginal ride pass subscription data from [City of Arlington \(CoA\)](#). A microtransit simulator with parametric dispatch policies developed by [Namdarpour et al. \(2024\)](#), called NOMAD-RPS, is calibrated to simulate the fleet of vehicles and quantify waiting and in-vehicle travel times. We focus on two revenue management scenarios. In the ride pass pricing policy scenario, we identify the optimal combination of interdependent weekly and monthly ride pass prices that maximizes total daily revenue. In the event- or place-based subsidy scenario, we evaluate the impact of targeted discounts on microtransit trips tied to places like hospitals or events like American football games, forecasting both the reduction in private vehicle usage and the additional subsidy required to sustain the discounted fares.

The remainder of the paper is organized as follows: [Section 2](#) introduces existing studies on microtransit simulation and demand forecasting, pointing out the current research gap and our contributions. [Section 3](#) introduces our methodology of estimating a nested nonparametric logit model and integrating it into a simulation framework. [Section 4](#) shows the results of an empirical study of Via microtransit in Arlington, TX. The final section concludes the key findings and discusses future work.

2. Literature review

2.1. Simulation-based frameworks for microtransit forecasting

The operational complexity of microtransit systems lies in dynamically optimizing vehicle routes and schedules to accommodate real-time trip requests, a challenge akin to solving dynamic pickup and delivery problems (PDPs) with stochastic demand ([Ho et al., 2018](#); [Ma et al., 2019](#)). Prior work has framed this as a vehicle routing problem with time windows (VRPTW) ([Desrochers et al., 1992](#)), where mixed-integer linear programming (MILP) models optimize fleet allocation under capacity and latency constraints ([Fu & Chow, 2022](#)), while nonlinear formulations incorporate fare elasticity and demand uncertainty ([Zhao et al., 2023](#)). Recent advances employ non-myopic dynamic routing algorithms to balance immediate service responses with fleet-level utilization. For instance, [Namdarpour et al. \(2024\)](#) considered opportunity costs in ride-pooling systems with synchronized transfers and demonstrated that operating without such considerations can significantly underperform.

Simulation-based frameworks are effective in evaluating microtransit systems under varying operational policies ([Jung & Chow, 2019](#); [Markov et al., 2021](#); [Yoon et al., 2022](#)). These frameworks typically employ vehicle routing algorithms and agent-based simulations to assess microtransit performance using traveler-centric metrics (e.g., waiting time, in-vehicle time,

rejection rates), operator-centric profits (e.g., operation cost and total revenue), and societal outcomes (e.g., mode shift and social welfare) (Calabrò et al., 2023; Leffler et al., 2024). Although a majority of simulation approaches focus on “within-day” fleet dynamics by mimicking only the real-time vehicle dispatching and rider matching under fixed demand (Costa et al., 2021), there is a growing number of studies that consider dynamic adaptation or “day-to-day” adjustment to capture the equilibrium between demand and supply sides (Caros & Chow, 2021). For instance, 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). Liu et al. (2019) introduced a Bayesian optimization framework to design mobility-on-demand services with endogenous demand and numerically showed the existence of supply-demand equilibrium. Rath et al. (2023) expanded the day-to-day adjustment process by handling first/last mile access trips and developing a synthetic scenario generation process, highlighting its potential in cross-city microtransit system evaluation. These frameworks have emerged as critical tools by explicitly capturing the interplay between system state and traveler behavior.

A significant limitation persists, however, in the estimation of microtransit travel demand. Most studies assume homogeneous or coarsely segmented user classes—such as distinguishing only between “cost-sensitive” and “time-sensitive” riders—which inadequately captures real-world behavioral diversity (Bills et al., 2022; Liu et al., 2019). This oversimplification ignores nuanced variations in individual sensitivities to attributes like fare, wait time, and reliability, leading to biased demand forecasts. For instance, models that aggregate preferences across income groups or trip purposes may fail to predict microtransit ridership among frequent commuters or sporadic users. Addressing this gap requires granular behavioral models that reflect individualized decision-making, enabling operators to tailor pricing and service strategies to heterogeneous traveler segments.

2.2. Behavioral models for microtransit demand estimation

Discrete choice models (DCMs) have been widely applied to forecast travel demand by analyzing travelers’ responses to various mobility options (see (Bowman & Ben-Akiva, 2001)). These models typically assume travelers make choices to maximize the overall utility they can expect to gain regarding attributes such as travel time, cost, or number of transfers. Relevant studies mainly use stated preference (SP) surveys to evaluate hypothetical adoption, comparing innovative mobility services (e.g., microtransit) against existing travel modes. For example, Yan et al. (2019) analyzed ride-sourcing adoption at the University of Michigan, linking income and car ownership to mode preferences. Monchambert (2020) assessed the attractiveness of an innovative carpooling service by comparing it with buses, trains, and cars, evaluating key attributes for both drivers and passengers. Rossetti et al. (2023) designed an SP survey to understand travelers’ preferences for first-mile/last-mile microtransit service in four cities in the U.S.: Miami, Minneapolis-Saint Paul, Washington, D.C., and Seattle. Despite their benefits, three limitations hinder current behavioral models in microtransit applications: (1) reliance on small-sample SP surveys, (2) parametric assumptions in estimating taste heterogeneity, and (3) a lack of such studies on subscription-related choice behavior.

First, data limitations pose a critical barrier. The nascent adoption of microtransit makes real-world behavioral data hard to collect, forcing existing studies to rely on SP surveys with limited sample sizes (Cavallaro et al., 2023). These surveys often overrepresent urban, tech-savvy early

adopters while underrepresenting low-income, rural, or disabled travelers, skewing preference estimates. A study of SmaRT Ride service in Sacramento revealed that low-income users faced such barriers as smartphone access and language differences, which were underrepresented in initial SP surveys (Xing et al., 2024). Although Kang et al. (2021) estimated a joint revealed-stated preference model for pooled ride-hailing services, their revealed-preference (RP) survey only included 594 individuals, whose representativeness for the whole city is still an issue.

Second, behavioral models for microtransit often oversimplify user preferences. While mixed logit (MXL) relaxes the assumption of homogeneous preferences in multinomial logit (MNL) by allowing taste parameters to follow arbitrary distributions (McFadden & Train, 2000), the mixing distribution is typically restricted to parametric forms (e.g., normal, uniform, or triangular distribution), which can be problematic when there are unobserved attributes related to service accessibility, environmental attitudes, and habitual behaviors (Hess, 2010; Sarrias, 2020). Alternatively, some studies have proposed semi-parametric or nonparametric approaches to capture taste heterogeneity in a more flexible manner, such as logit-mixed logit (Train, 2016), individual parameter logit (Swait, 2022), and agent-based mixed logit (Ren & Chow, 2022). However, these approaches have yet to be applied to microtransit demand modeling.

Third, a narrow research focus further limits practical relevance. Most studies prioritize mode and route choice, overlooking subscription programs that significantly impact car usage and drive long-term revenue (Hörcher & Graham, 2020). Subscription adoption (e.g., weekly/monthly ride passes) can improve microtransit usage through price anchoring and habit formation (Marino & Jayakrishnan, 2024). Empirical evidence in Arlington, TX shows that travelers ride 2.8 times more frequently and generate 1.7 times more revenue in the first week after holding ride passes than the previous week (Via, 2020). However, privacy constraints often restrict access to granular subscription data, making only aggregate adoption rates available, which are insufficient for estimating choice models in most cases. Consequently, although a small number of studies have considered subscription choice based on SP surveys (Bahamonde-Birke et al., 2023), almost none of them have linked individual-level subscription choice to trip-level mode choice at a large scale (i.e., across an entire city). Without capturing this higher-level behavior, microtransit operators may fail to design pricing policies that discount each ride in exchange for increased ridership, active engagement, and long-term revenue.

2.3. Our contributions

Building on the aforementioned limitations, we propose a nested nonparametric logit model for joint travel mode and ride pass subscription choice, which can be further integrated into a microtransit simulation framework.

The behavioral model advances microtransit demand estimation in three aspects. First, the model leverages synthetic population data and marginal subscription data to provide a citywide representation of microtransit trip demand, which is impossible with small-size SP survey data. The integration of a large dataset enhances the spatiotemporal granularity in microtransit choice modeling by capturing a broader range of travel behaviors across different demographics and geographic locations.

Second, the model captures taste heterogeneity using a nonparametric estimation approach (Ren & Chow, 2022), accounting for the impacts of sociodemographic and built-environment factors without requiring handcrafted model specifications where modelers have to determine how to specify each interaction term prior to model estimation (van Cranenburgh et al., 2022). This

allows for a more detailed analysis of user preferences at the population level, where general attitudes towards microtransit exist; at the individual level, where unique behavioral patterns are observed; and at the trip level, where such contextual factors as origins/destinations, day of week, and trip purpose influence choices.

Third, the model features a nested structure for joint travel mode and ride pass subscription choice. The parameters estimated from the lower-branch mode choice model are transformed into individual-level attributes in the upper-branch decision process, making it possible to estimate a subscription choice model using marginal ride pass data. This completes the loop of microtransit demand estimation, enabling policymakers to measure key behavioral responses, such as the elasticity of ride pass ownership w.r.t. microtransit service performance.

To showcase the potential of our model, we further integrated it into a simulation-based framework where supply-side service attributes (e.g., prices, in-vehicle/waiting times) dynamically interact with demand-side behavioral responses (e.g., mode shifts, subscription renewals). This advances revenue management with heterogeneous, reactive adjustments to subscription plan and fare discounting design.

3. Proposed methodology

The proposed methodology integrates joint subscription and mode choice modeling with dynamic microtransit simulation (Fig. 1). The lower-branch mode choice model uses an agent-based mixed logit (AMXL) approach to estimate travel mode decisions based on synthetic population data, capturing heterogeneous preferences for mode attributes such as travel time and cost. The upper-branch subscription choice model incorporates travelers' sensitivity to price and trip consumer surplus (CS) from the lower branch and applies a multinomial logit (MNL) model to match the predicted number of subscribers with marginal data. The model outputs feed into a simulation-based framework that iteratively updates perceived service performance to achieve user equilibrium, assessing the impact of microtransit subscription models and pricing strategies on microtransit revenue, mode shifts, and traveler benefits.

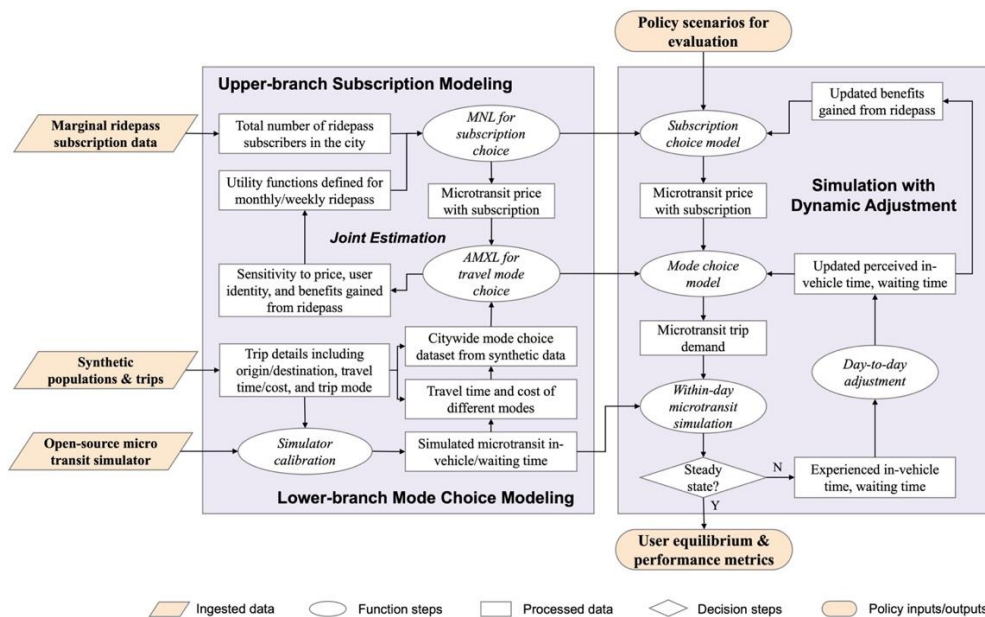


Fig. 1. A framework integrating choice modeling and microtransit simulation.

3.1. Architecture of microtransit behavioral model

We model microtransit-related choices as a nested structure. In the upper branch, individuals determine whether to purchase a weekly ride pass, a monthly ride pass, or no ride pass. By subscribing to a ride pass, travelers pay a fixed amount in advance and can take unlimited microtransit trips until the pass expires. Accordingly, subscription decisions are impacted by the cost of the ride pass and the utility gained from free microtransit trips after subscribing. The latter part comes from the lower branch, where individuals decide which mode to use conditional on the upper-branch decisions. In the lower branch, trips on weekdays and weekends are separated into two datasets. Two mode choice models are estimated to account for their divergent patterns. We assume individuals have different tastes on weekdays and weekends, and that weekday and weekend choices are independent of each other. The mode choice set includes traditional modes (e.g., driving, walking, biking, etc.) as well as microtransit. Factors such as travel time, trip purpose, tour type, and cost conditional on ride pass ownership impact the mode choice. The nested structure of our model is shown in Fig. 2. Notations used in the model are listed in Table 1.

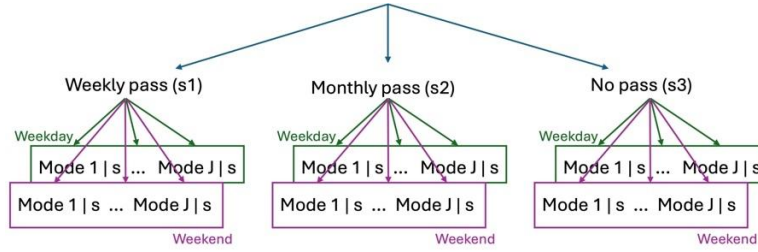


Fig. 2. The nested structure in the model.

Table 1

Notations used in the proposed model

N	A set of individuals indexed by individual ids
T	A set of trips indexed by trip origin-destination (OD) pair
S	A set of subscription alternatives
J	A set of mode alternatives including microtransit
P	A set of trip purpose
Q	A set of tour type
$U_{n,weekly}, \epsilon_{n,weekly}$	Total and random utilities of individual n purchasing weekly ride pass
$U_{n,monthly}, \epsilon_{n,monthly}$	Total and random utilities of individual n purchasing monthly ride pass
$U_{n,none}, \epsilon_{n,none}$	Total and random utilities of individual n not purchasing any ride pass
$U_{n,MT,t}, \epsilon_{n,MT,t}$	Total and random utilities of individual n choosing microtransit in trip t
$U_{n,j,t}, \epsilon_{n,j,t}$	Total and random utilities of individual n choosing mode j in trip t
$V_{n,s}$	Systematic utility if individual n choosing ride pass option j
$V_{n,j,t}$	Systematic utility of individual n choosing mode j in trip t
$V_{n,j,t}^{rp}, V_{n,j,t}^{nrp}$	Systematic utility of individual n choosing mode j in trip t with/without a ride pass
$Price_{weekly}, Price_{monthly}$	Prices of weekly and monthly ride pass
$Gain_n^{we}, Gain_n^{wd}$	“Benefits” gained from holding a ride pass on weekdays/weekends
MT_n	A binary variable indicating if individual n is a microtransit user

$TT_{MT,t}, TT_{j,t}$	Travel time of microtransit/mode j in trip t
$WT_{MT,t}$	Waiting time of microtransit in trip t
$COST_{n,MT,t}$	Microtransit fare (distance-based) charged to individual n for trip t
$COST_{j,t}$	Fare of other mode j in trip t
$SH_{n,t}$	A binary variable indicating if individual n 's trip t is for shopping
$SC_{n,t}$	A binary variable indicating if individual n 's trip t is to school
$OT_{n,t}$	A binary variable indicating if individual n 's trip t serves other purposes
$COM_{n,t}$	A binary variable indicating if individual n 's trip t is part of a commute tour
$NCOM_{n,t}$	A binary variable indicating if individual n 's trip t is part of a non-commute tour
$\beta_{price,n}$	Individual-level parameter of ride pass price
$\beta_{tt,n}$	Individual-level parameter of travel time
$\beta_{wt,n}$	Individual-level parameter of microtransit waiting time
$\beta_{cost,n}$	Individual-level parameter of travel cost
$asc_{MT,t}, asc_{j,t}$	Trip OD-level mode-specific constants
$\beta_{shopping}$	Generic parameter of trips for shopping
β_{school}	Generic parameter of trips to school
β_{other}	Generic parameter of trips serving other purpose
$\beta_{commute}$	Generic parameter of trips in commute tours
β_{noncom}	Generic parameter of trips in non-commute tours
$\beta_{gain}^{we}, \beta_{gain}^{wd}$	Generic parameter of “benefits” gained on weekdays/weekends
$\beta_{MT-user}$	Generic parameter of microtransit user
$asc_{weekly}, asc_{monthly}$	Generic ride pass-specific constants
f_{rp}	Generic factor linking the parameters of travel cost and ride pass price

3.1.1. Upper-branch subscription choice model

We consider three alternatives according to current subscription programs: subscribing to a weekly ride pass, subscribing to a monthly ride pass, and opting not to subscribe to a ride pass. From a weekly perspective, the utility of individual n choosing these alternatives are defined in Eqs. (1) – (3).

$$U_{n,weekly} = \beta_{price,n}Price_{weekly} + \beta_{gain}^{we}Gain_n^{we} + \beta_{gain}^{wd}Gain_n^{wd} + \beta_{MT-user}MT_n + asc_{weekly} + \varepsilon_{n,weekly}, \quad \forall n \in N \quad (1)$$

$$U_{n,monthly} = \beta_{price,n}Price_{monthly}/4 + \beta_{gain}^{we}Gain_n^{we} + \beta_{gain}^{wd}Gain_n^{wd} + \beta_{MT-user}MT_n + asc_{monthly} + \varepsilon_{n,monthly}, \quad \forall n \in N \quad (2)$$

$$U_{n,none} = \varepsilon_{n,none}, \quad \forall n \in N \quad (3)$$

where $U_{n,weekly}$, $U_{n,monthly}$, and $U_{n,none}$ denote individual n 's utility per week by subscribing to a weekly, monthly, and no ride pass. $Price_{weekly}$ and $Price_{monthly}$ are the prices of the ride pass (the price of monthly ride pass is divided by 4 to obtain the cost per week). $\beta_{price,n}$ is a parameter reflecting individual n 's sensitivity to price. $Gain_n^{we}$ and $Gain_n^{wd}$ denote the benefits gained from free microtransit trips by holding a ride pass, which depend on individual n 's microtransit trip frequency on weekday (we) and weekend (wd). β_{gain}^{we} , β_{gain}^{wd} are parameters reflecting the general sensitivity to these gained benefits. MT_n is a binary variable indicating whether individual n has

experience riding microtransit before, and $\beta_{MT-user} > 0$ is its parameter assuming that individuals who have used microtransit have a higher probability to purchase ride pass. asc_{weekly} and $asc_{monthly}$ are alternative specific constants of weekly and monthly ride pass. $\varepsilon_{n,weekly}$, $\varepsilon_{n,monthly}$, and $\varepsilon_{n,none}$ are independent and identically distributed (i.i.d.) random utilities following a Gumbel distribution. The probability of individual n choosing subscription option s can be computed using the multinomial logit (MNL) form.

The primary challenge in estimating this model as a stand-alone MNL model is that only marginal subscription data are available due to privacy concerns. This limitation makes attributes such as $Gain_n^{we}$, $Gain_n^{wd}$, MT_n difficult to measure and renders the individual parameter $\beta_{price,n}$ infeasible to estimate. However, it is possible to obtain this information from a lower-branch mode choice model estimated using large-scale travel data from synthetic populations/trips and advanced estimation approaches. In that case, $Gain_n^{we}$, $Gain_n^{wd}$, MT_n , and $\beta_{price,n}$ can be obtained from the choice observations and taste parameters from the lower branch, as shown in Eqs. (4) – (6).

$$Gain_n^d = \sum_{t \in T_n^d} \left(\ln \sum_{j \in J} e^{V_{n,j,t}^{rp}/\beta_{gain}^d} - \ln \sum_{j \in J} e^{V_{n,j,t}^{nrp}/\beta_{gain}^d} \right), \quad \forall n \in N, d \in \{we, wd\} \quad (4)$$

$$MT_n = 1(\sum_{t \in T} 1(j_{n,t} = MT) > 0), \quad \forall n \in N \quad (5)$$

$$\beta_{price,n} = f_{rp} \beta_{tt,n}, \quad \forall n \in N \quad (6)$$

where $d \in \{we, wd\}$ indicates the day of the week, T_n^d is the set of trips made by individual n on day d , J is the mode choice in the lower branch, $V_{n,j,t}^{rp}$ represents the systematic utility with ride pass trip discounts, and $V_{n,j,t}^{nrp}$ represents the systematic utility without ride pass trip discounts. Eq. (4) indicates that the “benefits” gained from holding a ride pass are measured as the logsum utility or inclusive value (Ben-Akiva & Lerman, 1985) in the lower branch. The terms $\ln \sum_{j \in J} e^{V_{n,j,t}^{rp}/\beta_{gain}^d}$ and $\ln \sum_{j \in J} e^{V_{n,j,t}^{nrp}/\beta_{gain}^d}$ represent the inclusive values for the nests with and without ride pass, respectively. The parameters β_{gain}^{wd} and β_{gain}^{we} serve as two nesting parameters that scale the mode choice utilities on weekdays and weekends. Eq. (5) ensures that individual n is classified as a microtransit user if the individual has at least one observed microtransit trip in the lower-branch choice dataset, where $1(\cdot)$ is an indicator function that returns 1 if the condition in the parentheses holds and 0 otherwise. Eq. (6) links the individual n ’s sensitivity to trip cost with the sensitivity to the ride pass price by introducing a generic parameter f_{rp} , which reflects the proportional relationship between individuals’ valuation of per-trip costs and their willingness to pay for a ride pass.

3.1.2. Lower-branch mode choice model

In the mode choice scenario, we differentiate the utility function of choosing microtransit from other modes (e.g., driving, public transit, driving, walking), conditional on the subscription plan choice. For each trip $t \in T$ made by individual $n \in N$ on a weekday or a weekend, the utility functions choosing microtransit and other modes are defined in Eqs. (7) – (8).

$$V_{n,MT,t|s} = \beta_{tt,n} TT_{MT,t} + \beta_{wt,n} WT_{MT,t} + Y_{n,none} \beta_{cost,n} COST_{n,MT,t} + \sum_{p \in P} \beta_p Purp_{n,p,t} + \sum_{q \in Q} \beta_q Tour_{n,q,t} + asc_{MT,t}, \quad \forall n \in N, t \in T \quad (7)$$

$$V_{n,j,t|s} = V_{n,j,t} = \beta_{tt,n} TT_{j,t} + \beta_{cost,n} COST_{j,t} + asc_{j,t}, \quad \forall n \in N, j \in J, j \neq MT, t \in T \quad (8)$$

where $V_{n,MT,t|s}$ is the systematic utility of choosing microtransit, which is conditional on individual n 's subscription choice s . $TT_{MT,t}$ denotes microtransit travel time, $WT_{MT,t}$ denotes microtransit waiting time, and $COST_{MT,t}$ denotes microtransit trip fare based on fare schedules. $Y_{n,none}$ is a binary variable indicating if individual n does not subscribe to a ride pass at the upper branch. Eq. (7) ensures that when $Y_{n,none} = 0$, the microtransit utility corresponds to a ride pass scenario, $V_{n,j,t}^{rp}$, and when $Y_{n,none} = 1$, the microtransit utility corresponds to the non-ride pass scenario, $V_{n,j,t}^{nrp}$. Eq. (8) defines the systematic utility of choosing other mode $j \in J$. We include several dummy variables to consider the effects of trip purpose and tour type on the preference of microtransit over other modes. $Purp_{n,p,t}$ is a dummy variable indicating whether trip t made by individual n serves purpose p . $Tour_{n,q,t}$ is a dummy variable indicating whether trip t made by individual n is part of a tour with type q . P is the set of trip purposes such as working or shopping. Q is the set of such tour types as commuting tour or home-based tour.

$\beta_{tt,n}$, $\beta_{wt,n}$, and $\beta_{cost,n}$ represent travel time and cost parameters, which are assumed to vary across individuals. $asc_{MT,t}$ and $asc_{j,t}$ denote alternative-specific constants, which are assumed to vary across trip origin-destination (OD) pairs. $\beta_p, p \in P$ and $\beta_q, q \in Q$ are parameters of trip purpose and tour type, which are assumed to be homogeneous across individuals and trips. By allowing a nonparametric distribution at different levels, we account for the influence of sociodemographic and built-environment factors without requiring handcrafted model specifications where modelers have to determine how to specify each interaction term prior to model estimation (van Cranenburgh et al., 2022). The model makes sense when (1) the choice dataset is sufficiently large, and (2) we only want to make predictions for the same population. In those cases, it is unnecessary to assume a parametric distribution to transfer from a sample to the population.

Based on the nested structure, the probability of individual n choosing subscription option s and use mode j in trip t can be defined in Eqs. (9) – (11).

$$P_{n,s,j,t} = P_{n,s} P_{n,j,t|s}, \quad \forall n \in N, s \in S, j \in J, t \in T \quad (9)$$

$$P_{n,s} = \frac{e^{V_{n,s}}}{\sum_{s' \in S} e^{V_{n,s'}}}, \quad \forall n \in N, s \in S \quad (10)$$

$$P_{n,j,t|s} = \frac{e^{V_{n,j,t|s}}}{\sum_{j' \in J} e^{V_{n,j',t|s}}}, \quad \forall n \in N, s \in S, j \in J, t \in T \quad (11)$$

where S is the choice set of ride pass options and J is the choice set of travel modes. $P_{n,s}$ denotes the probability in the upper branch and $P_{n,j,t|s}$ denotes the probability in the lower branch.

3.2. Proposed estimation algorithm

Following the work of [Ren and Chow \(2022\)](#), we employ an agent-based mixed logit (AMXL) approach to estimate the lower-branch mode choice model for each individual and trip. In AMXL, each trip t made by individual n is represented as an agent, whose parameters ($\beta_{n,t}$) can be jointly and nonparametrically estimated by solving a multiagent inverse utility maximization (MIUM) problem under L_2 -norm as a convex quadratic programming (QP) problem. We extend the approach of [Ren and Chow \(2022\)](#) by introducing additional constraints to ensure the consistency of parameters among individuals and trips, thereby enhancing model flexibility by allowing parameters to vary at different levels. The formulation of the estimation problem is shown in [Eqs. \(12\) – \(18\)](#).

$$\min_{\beta_0, \beta_{n,t}} \sum_{n \in N} \sum_{t \in T} (\beta_0 - \beta_{n,t})^2 \quad (12)$$

subject to:

$$V_{n,j^*,t} + \varepsilon_{n,j^*,t} \geq V_{n,j,t} + \varepsilon_{n,j,t} + b, \quad \forall n \in N, t \in T, j, j^* \in J, j \neq j^* \quad (13)$$

$$\beta_{n,t} \geq lb, \quad \forall n \in N, t \in T \quad (14)$$

$$\beta_{n,t} \leq ub, \quad \forall n \in N, t \in T \quad (15)$$

$$\beta_{k,n} = \frac{1}{|T|} \sum_{t \in T} \beta_{n,t}, \quad \forall n \in N, k \in K_{individual} \quad (16)$$

$$\beta_{k,t} = \frac{1}{|N|} \sum_{n \in N} \beta_{n,t}, \quad \forall t \in T, k \in K_{trip} \quad (17)$$

$$\beta_{k,0} = \frac{1}{|N||T|} \sum_{n \in N} \sum_{t \in T} \beta_{n,t}, \quad \forall k \in K \quad (18)$$

where K is the set of parameters in the mode choice model, β_0 is a vector of $|K|$ population-level parameters, and $\beta_{n,t}$ is a vector of $|K|$ agent-level parameters. $K_{individual}$ is the set of parameters varying across individuals and K_{trip} is the set of parameters varying across trips. [Eq. \(12\)](#) defines the objective function, which is to minimize the variance of agent-level parameters. [Eq. \(13\)](#) ensures that the observed choice j^* maximizes the individual n 's utility in trip t , where b is a safety margin with a recommended value around a predefined percentile of $(\varepsilon_{n,j^*,t} - \varepsilon_{n,j,t})$. [Eqs. \(14\) – \(15\)](#) determine the parameter boundaries for estimation, where lb and ub are vectors specifying the lower and upper bounds. [Eq. \(16\)](#) ensures that individual-level parameters vary only across individuals. [Eq. \(17\)](#) ensures that trip-level parameters vary only across trips. [Eq. \(18\)](#) ensures that population-level (or generic) parameters are the average of agent-level parameters.

Solving the MIUM problem as a single QP problem would be computationally costly as it would lead to a highly sparse diagonal matrix. Instead, AMXL uses a decomposition method to initialize β_0 and update $\beta_0, \beta_{n,t}$ iteration by iteration. The subproblem with a fixed β_0 can be solved using any optimizer software or package that can handle QP like Gurobi, CVXPY, etc. The estimation algorithm is summarized in [Algorithm 1](#).

Algorithm 1. Parameter estimation in the mode choice model

1. Given observed variables and mode choice, initialize with $i = 0$ and population-level parameters $\beta_0^{(i)} = [0, 0, \dots, 0]$.
 2. For each trip $t \in T$ made by individual $n \in N$, solve a QP problem get $\beta_{n,t}^{(i)}$:
$$\min_{\beta_0, \beta_{n,t}} (\beta_0 - \beta_{n,t})^2 \text{ subject to constraints in Eqs. (13) – (15).}$$
 3. Calculate individual-level parameters ($\beta_{k,n}$) and trip-level parameters ($\beta_{k,t}$) using Eqs. (16) – (17).
 4. Set average to $y_0^{(i)} = \frac{1}{|N||T|} \sum_{n \in N} \sum_{t \in T} \beta_{k,t}$ as shown in Eq. (18).
 5. Use Method of Successive Averages (Sheffi & Powell, 1982) to update population-level parameters and get $\beta_0^{(i+1)}$:
$$\beta_0^{(i+1)} = \frac{i}{i+1} \beta_0^{(i)} + \frac{1}{i+1} y_0^{(i)}$$
 6. If the stopping criteria (percentage change smaller than 0.1%) for β_0 reached, stop and output $\beta_0^{(i)}, \beta_{n,t}^{(i)}$; else, set $i = i + 1$ and go back to Step 2.
-

Since only marginal subscription data is available at the upper branch, it is impossible to use maximum loglikelihood estimation (MLE) to estimate a choice model. Instead, we calibrate the six subscription choice parameters (f_{RP} , β_{gain}^{we} , β_{gain}^{wd} , $\beta_{MT-user}$, asc_{weekly} , $asc_{monthly}$) by formulating a least squares optimization problem that minimize the gap between predicted and observed number of subscribers. The optimization problem is shown in Eqs. (19) – (21).

$$\min_{\beta_{ridepass}} \sum_{j \in J_{ridepass}} \left(Num_j - \sum_{n \in N} P_{n,j} \right)^2 \quad (19)$$

subject to:

$$P_{n,j} = \frac{e^{V_{n,j}}}{\sum_{j' \in J_{ridepass}} e^{V_{n,j'}}}, \quad \forall n \in N, j \in J_{ridepass} \quad (20)$$

$$V_{n,j} = \beta_{ridepass}^T X_{n,j}, \quad \forall n \in N, j \in J_{ridepass} \quad (21)$$

where $\beta_{ridepass}$ is a vector of six parameters serving as decision variables, $J_{ridepass}$ is the choice set that includes weekly, monthly, and none ride pass options, and Num_j represents the observed number of individuals choosing a ride pass option. Eq. (19) defines the objective function, which is to minimize the squared error of predicted subscribers. Eq. (20) ensures that the probability $P_{n,j}$ is computed using the multinomial logit (MNL) form. Eq. (21) ensures that the systematic utility $V_{n,j}$ equals the sum-product between vectors of parameters $\beta_{ridepass}$ and attributes $X_{n,j}$ defined in Eqs. (1) – (3). We solve the optimization problem using the Generalized Reduced Gradient (GRG) nonlinear algorithm (Lasdon et al., 1974), which is one of the default methods in the solver tool in Microsoft Excel. Since our objective function is nonconvex, the GRG nonlinear algorithm has the risk of getting stuck at a local optimum. To reduce such an impact, we set bounds $[-10, 10]$ for the ride pass parameters to avoid extreme values, and employ a multi-start routine and observe that the results from different starting points do not change significantly in our experiments.

Estimating the lower and upper branches separately does not make sense since they are interrelated, i.e., subscription choice in the upper branch impacts microtransit trip fares, while mode choice in the lower branch provides information about gained benefits, microtransit user identity, and sensitivity to ride pass price. Hence, we propose a new iterative algorithm to estimate them jointly. We start from assuming no individual holds a ride pass and setting initial parameters to zero. In each iteration, we estimate the lower-branch mode choice model with current microtransit trip fares, pass $Gain_n^{we}$, $Gain_n^{wd}$, MT_n , and $\beta_{price,n}$ to the upper-branch to estimate the subscription choice model, scale the lower-branch parameters using the nesting parameters, update the choice parameters using the Method of Successive Average (MSA), and recalculate microtransit trip fares with the predicted ride pass ownership. This iterative process continues until the stopping criterion is satisfied. The joint estimation approach is summarized in [Algorithm 2](#).

Algorithm 2. Joint estimation of subscription choice and mode choice

1. Initialize with no individual holding weekly or monthly ride pass ($P_{n,none} = 1, \forall n \in N$), calculate microtransit trip fares without a ride pass, and set $\beta_{ridepass}$, $\beta_{n,t}^{we}$, $\beta_{n,t}^{wd}$ to zero.
 2. Estimate two lower-branch mode choice models (one for weekdays and the other for weekends) using [Algorithm 1](#) and get parameters $\tilde{\beta}_{n,t}^{we}$, $\tilde{\beta}_{n,t}^{wd}$.
 3. Calculate $Gain_n^{we}$, $Gain_n^{wd}$, MT_n , and $\beta_{price,n}$ based on [Eqs. \(4\)-\(6\)](#).
 4. Estimate the upper-branch subscription choice model by solving the problem in [Eqs. \(19\)-\(21\)](#) and get $\beta_{ridepass}$.
 5. Scale mode choice parameters using nesting parameters:

$$\beta_{n,t}^{we} = \tilde{\beta}_{n,t}^{we} \beta_{gain}^{we}, \quad \beta_{n,t}^{wd} = \tilde{\beta}_{n,t}^{wd} \beta_{gain}^{wd}, \quad \forall n \in N, t \in T$$
 6. Update $\beta_{ridepass}$, $\beta_{n,t}^{we}$, $\beta_{n,t}^{wd}$ using Method of Successive Averages (MSA).
 7. If the stopping criteria (percentage change smaller than some tolerance) for $\beta_{ridepass}$, $\beta_{n,t}^{we}$, $\beta_{n,t}^{wd}$ reached, stop and output these parameters; else recalculate microtransit trip fares with predicted ride pass ownership and go back to Step 2.
-

3.3. Simulation-based framework with the behavioral model

3.3.1. Within-day microtransit simulator

A key part of the framework is the within-day microtransit simulator, which is designed to simulate trip-level microtransit in-vehicle and waiting times based on incoming trip requests, while considering congestion and queueing effects. We use an open-source simulator developed by [Namdarpour et al. \(2024\)](#), NOMAD-RPS, which takes microtransit trip requests as input and outputs service performance metrics by determining which vehicles to dispatch and transport passengers from their origins to their destinations. We selected NOMAD-RPS for two reasons: (1) it is open source with a well-maintained GitHub repository (<https://github.com/BUILTNYU/ridepooling>), and (2) it employs a parametric non-myopic cost function approximation policy to sequentially find the best matches between riders and vehicles, which can be calibrated to real-world fleet operations.

Several parameters should be calibrated to ensure the simulator accurately reflects a specific microtransit system. These parameters include number of vehicles, maximum passenger walking time, maximum passenger waiting time, the balance between operator and user cost, and the degree of lookahead approximation employed. Calibration of these parameters can be conducted by

comparing simulation outputs with observed performance metrics from real-world microtransit services, such as average in-vehicle time, average waiting time, and average vehicle occupancy.

3.3.2. Dynamic adjustment process

A day-to-day process characterizes the dynamics in adjustments made by both travelers and operators each day as a dynamic system (Rath et al., 2023). Djavadian and Chow (2017) showed that such adjustment processes can reach a stochastic user equilibrium (SUE) to simulate on-demand systems. However, existing studies have neither incorporated nonparametric mode choice parameters into microtransit demand estimation nor considered ride pass subscription choices at a higher level.

The process introduced by Rath et al. (2023) is modified to address the requirements of our framework. In our process, only travelers are allowed to adjust their behavior, whereas prices and operational decisions from the operator side are treated as explicit attributes. The adjustment process is also modified to incorporate both mode and subscription choices, such that perceived microtransit in-vehicle and waiting times not only influence mode selection, but also determine the benefits derived from ride pass and consequently affect ride pass ownership. The right part of Figure 1 illustrates the whole process.

At the start of the simulation, a policy scenario is defined as the input, specifying operational decisions such as ride pass pricing, fare schedules, and fleet size. The microtransit fare for each trip is then calculated based on trip origins and destinations as well as predicted ride pass ownership. Travelers subsequently make their mode choices by evaluating trip fares and perceived service attributes, including in-vehicle and waiting times. These mode decisions generate the microtransit trip requests in the within-day microtransit simulator. Microtransit in-vehicle and waiting times are updated from day to day. A traveler n who used microtransit on day d learns from his/her experience on the day and updates their perceived in-vehicle and waiting times with a learning rate θ , as shown in Eqs. (22) – (23).

$$TT_{MT,n}^{d+1} = (1 - \theta)TT_{MT,n}^d + \theta ETT_{MT,n}^d, \quad \forall n \in N_{MT} \quad (22)$$

$$WT_{MT,n}^{d+1} = (1 - \theta)WT_{MT,n}^d + \theta EWT_{MT,n}^d, \quad \forall n \in N_{MT} \quad (23)$$

where N_{MT} is the set of microtransit users. $TT_{MT,n}^d$ and $WT_{MT,n}^d$ denote perceived microtransit in-vehicle time and waiting time for user n at the beginning of day d . $ETT_{MT,n}^d$ and $EWT_{MT,n}^d$ represent experienced microtransit in-vehicle time and waiting time obtained from the microtransit simulator. For travelers who did not use microtransit, their perceived times are updated with the population's average perceived times which is the successive average of average times in the past days. For instance, the population's perceived in-vehicle time on day d (\overline{TT}_{MT}^d) is defined in Eqs. (24) – (25).

$$\overline{TT}_{MT}^d = \left(1 - \frac{1}{d}\right) \overline{TT}_{MT}^{d-1} + \frac{1}{d} E\overline{TT}_{MT}^d \quad (24)$$

$$E\overline{TT}_{MT}^d = \frac{1}{|N_{MT}|} \sum_{n \in N_{MT}} ETT_{MT,n}^d \quad (25)$$

At the end of each day (or iteration), we update $Gain_n^{we}$, $Gain_n^{wd}$, MT_n , and the ride pass ownership prediction, and then check whether the system has reached a steady state. The adjustment stops when the change of microtransit ridership and ride pass ownership is below 1%. We recall the proposition from [Djavadian and Chow \(2017\)](#) where the agent-based day-to-day process with a Method of Successive Averages (MSA) converges almost surely to a stochastic user equilibrium (SUE).

3.4. Consumer surplus, elasticity, and key metrics

3.4.1. Consumer surplus and elasticity

Based on the parameters from the behavioral model, we calculate the *consumer surplus* ([Chipman & Moore, 1980](#)) of subscription choice and mode choice, as shown in [Eqs.\(26\) – \(27\)](#).

$$CS_{n,S} = -\frac{1}{\beta_{price,n}} \ln \left(\sum_{s \in S} e^{V_{n,s}} \right) + C_{n,S}, \quad \forall n \in N \quad (26)$$

$$CS_{n,J,t}^d = -\frac{1}{\beta_{cost,n}^d} \ln \left(\sum_{j \in J} e^{V_{n,j,t}^d / \beta_{gain}^d} \right) + C_{n,J}^d, \quad \forall n \in N, d \in \{we, wd\} \quad (27)$$

where $CS_{n,S}$ represents the consumer surplus of subscription choice. One over the ride pass price parameter $-\frac{1}{\beta_{price,n}}$ is used to convert it into monetary units (dollars). $CS_{n,J,t}^d$ represents the consumer surplus of mode choice on weekdays or weekends. One over the travel cost parameter $-\frac{1}{\beta_{cost,n}^d}$ is used to convert it into monetary units (dollars). $C_{n,S}$ and $C_{n,J}^d$ are arbitrary constants, so the absolute surplus is less meaningful than surplus differences between scenarios. The value of ride pass plans and microtransit service can be measured using the difference in consumer surplus between two scenarios: one with these alternatives and one without, as shown in [Eqs. \(28\) – \(29\)](#).

$$CV_{n,S \rightarrow S^-} = CS_{n,S} - CS_{n,S^-}, \quad \forall n \in N \quad (28)$$

$$CV_{n,J \rightarrow J^-,t}^d = CS_{n,J,t}^d - CS_{n,J^-,t}^d, \quad \forall n \in N, d \in \{we, wd\} \quad (29)$$

where CV denotes the compensating variation—the amount an individual should be compensated to be as well off as before a scenario change ([Small & Rosen, 1981](#)). S is the subscription choice set that includes ride pass options, while S^- is the set that only includes the no-ride-pass option. J is the mode choice set that includes microtransit, while J^- is the set excluding microtransit.

Moreover, we calculate the *elasticity* of ride pass ownership (weekly pass and monthly pass) with respect to microtransit service performance (in-vehicle time and waiting time on weekdays and weekends). For instance, the elasticity of an individual n 's probability of purchasing weekly ride pass ($P_{n,weekly}$) w.r.t. microtransit waiting time of trip t on weekday ($WT_{MT,t}^{we}$) is defined in [Eqs.\(30\) – \(32\)](#).

$$E_{WT_{MT,t}^{we}}^{P_{n,weekly}} = \frac{\partial P_{n,weekly}}{\partial Gain_n^{we}} \cdot \frac{\partial Gain_n^{we}}{\partial WT_{MT,t}^{we}} \cdot \frac{WT_{MT,t}^{we}}{P_{n,weekly}}, \quad \forall n \in N, t \in T \quad (30)$$

$$\frac{\partial P_{n,weekly}}{\partial Gain_n^{we}} = P_{n,weekly}(1 - P_{n,weekly})\beta_{gain}^{we}, \quad \forall n \in N \quad (31)$$

$$\begin{aligned} \frac{\partial Gain_n^{we}}{\partial WT_{MT,t}^{we}} &= \frac{\partial \sum_{t \in T_n^{we}} (\ln(\sum_{j \in J} e^{V_{nj,t}^{rp}}) - \ln(\sum_{j \in J} e^{V_{nj,t}^{nrp}}))}{\partial WT_{MT,t}^{we}} \\ &= \frac{1}{\sum_{j \in J} e^{V_{nj,t}^{rp}}} \cdot e^{V_{n,MT,t}^{rp}} \cdot \beta_{wt,n}^{we} - \frac{1}{\sum_{j \in J} e^{V_{nj,t}^{nrp}}} \cdot e^{V_{n,MT,t}^{nrp}} \cdot \beta_{wt,n}^{we} \\ &= \beta_{wt,n}^{we}(P_{n,MT,t}^{rp} - P_{n,MT,t}^{nrp}), \quad \forall n \in N, t \in T \end{aligned} \quad (32)$$

where $E_{WT_{MT,t}^{we}}^{P_{n,weekly}}$ represents the elasticity, $Gain_n^{we}$ represents the “benefits” gained from holding a ride pass on weekdays, $\frac{\partial P_{n,weekly}}{\partial Gain_n^{we}}$ represents the partial derivative of $P_{n,weekly}$ w.r.t. $Gain_n^{we}$ derived from the upper-branch model, and $\frac{\partial Gain_n^{we}}{\partial WT_{MT,t}^{we}}$ represents the partial derivative of $Gain_n^{we}$ w.r.t. $WT_{MT,t}^{we}$ derived from the lower-branch model. $P_{n,MT,t}^{rp}$ and $P_{n,MT,t}^{nrp}$ represent the probability of choosing microtransit with and without a ride pass. $\beta_{wt,n}^{we}$ is individual n 's parameter of microtransit waiting time on weekdays.

3.4.2. Key metrics for policy evaluation

Once the simulation reaches a steady state, several key metrics are calculated for policy evaluation. *Daily microtransit ridership (DMR)* is computed by summing the trip-level probabilities of choosing microtransit. To derive the daily microtransit ridership (trips/day), we average weekday and weekend ridership based on the respective number of days in a week, as shown in Eq. (33).

$$DMR = \frac{5}{7} \sum_{n \in N} \sum_{t \in T^{we}} Y_{n,MT,t} + \frac{2}{7} \sum_{n \in N} \sum_{t \in T^{wd}} Y_{n,MT,t} \quad (33)$$

where $Y_{n,MT,t}$ is a binary variable indicating whether individual n chooses microtransit in trip t , T^{we} is the set of weekday trips, and T^{wd} is the set of weekend trips.

Total number of subscribers (TNS) is computed by summing the number of individuals subscribing weekly and monthly ride pass, as shown in Eq. (34).

$$TNS = NS_{weekly} + NS_{monthly} = \sum_{n \in N} Y_{n,weekly} + \sum_{n \in N} Y_{n,monthly} \quad (34)$$

where $Y_{n,weekly}$ and $Y_{n,monthly}$ are binary variables indicating whether individual n purchases a weekly ride pass or a monthly ride pass, respectively.

Total daily revenue (TDR) is measured in units of dollars per day (\$/day) and consists of revenue collected from trip fares and ride pass subscriptions, as shown in Eq. (35). To calculate trip fare revenue, we only consider microtransit trips made by non-subscribers since microtransit service is free to ride pass subscribers. Daily ride pass revenue is calculated by dividing weekly ride pass revenue by 7 and monthly ride pass revenue by 30, and then summing these two amounts.

$$TDR = \frac{5}{7} \sum_{n \in N_{none}} \sum_{t \in T^{we}} COST_{MT,t} Y_{n,MT,t} + \frac{2}{7} \sum_{n \in N_{none}} \sum_{t \in T^{wd}} COST_{MT,t} Y_{n,MT,t} + \frac{1}{7} Price_{weekly} NS_{weekly} + \frac{1}{30} Price_{monthly} NS_{monthly} \quad (35)$$

where N_{none} is the set of non-subscribers, $COST_{MT,t}$ denotes the microtransit trip fare based on fee schedules, $Price_{weekly}$ denotes the price of weekly ride pass, and $Price_{monthly}$ denotes the price of monthly ride pass.

4. Case study: Via Microtransit in Arlington, TX

In this section, we apply the proposed methodology to a case study in Arlington, TX. With a population of 0.4 million, Arlington is one of the largest U.S cities without a fixed-route public transit system. In December 2017, the city launched a public-private partnership for microtransit operated by Via, making it Arlington's sole public transit option, and the first city in the U.S. to adopt microtransit as the primary mode of public transport (Via, 2020). The service has expanded annually, and in 2021, the city contracted Via to operate approximately 70 six-passenger minivans covering the entire city. Travelers can summon a vehicle with a 12-15 minute waiting time and pay a fare ranging from \$3 to \$5 per trip (based on trip distance) or subscribe to a weekly ride pass (\$25 per week) or a monthly ride pass (\$80 per week). These features make Via Arlington an ideal case study.

4.1. Setup of experiments

4.1.1. Data collection

The synthetic population dataset provided by [Replica Inc.](#) comprises 1.35 million trips (0.70 million on a typical weekday and 0.65 million on a typical weekend) made by 0.4 million Arlington residents in Q2 2023. The dataset includes trip details such as origin and destination, mode, distance, duration, and cost. The dataset was generated using a combination of mobile location data, resident demographics, built environment data, and economic activity data. The data quality report is available at the census level for the entire U.S. region ([Replica Inc., 2022](#)). According to the report, the largest error in demographic attributes for a single census tract unit is within 5% compared to census data, while the largest error in commute mode share for a single census tract unit is within 10% compared to Census Transportation Planning Products (CTPP) data. [Fig. 3](#) shows census block group-level OD pairs with more than 50 trips per day, illustrating diverse travel patterns on weekdays and weekends across four mutually exclusive population segments:

- *Not-low-income segment*: Individuals younger than 65, not enrolled in school, and above the U.S. Federal Poverty Level ([ASPE, 2023](#)), accounting for 54.52% of total population.

- *Low-income segment*: Individuals younger than 65, not enrolled in school, and below the U.S. Federal Poverty Level, accounting for 11.56% of total population.
- *Senior segment*: Individuals aged 65 and older, accounting for 10.25% of total population.
- *Student segment*: Individuals currently enrolled in school, accounting for 23.67% of total population.

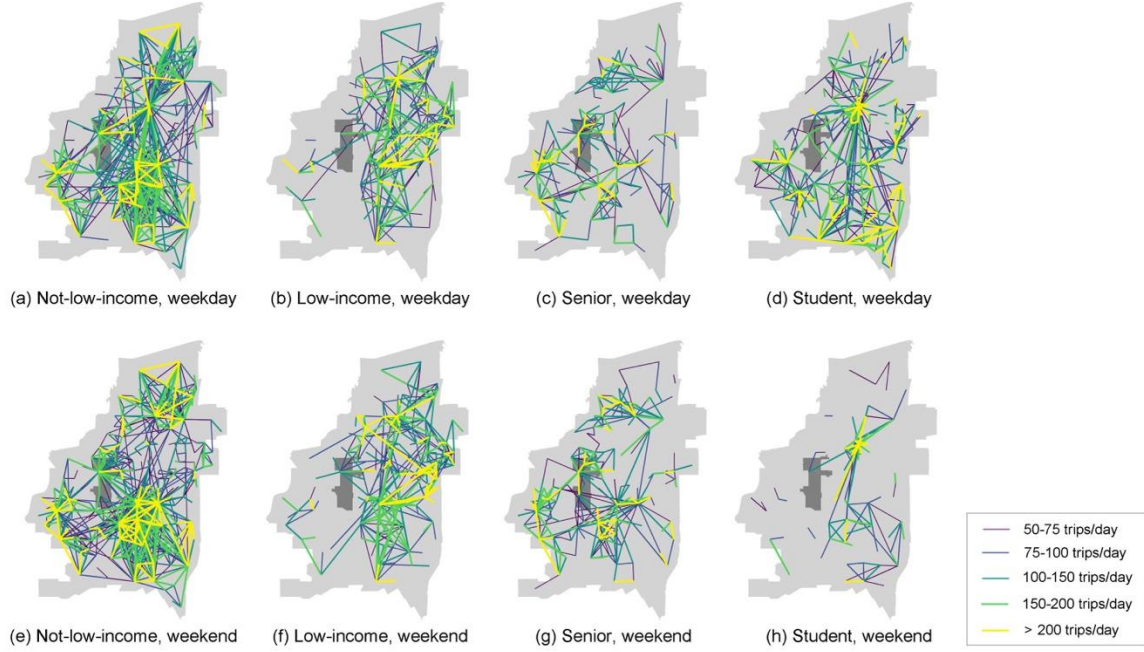


Fig. 3. Trips made by four population segments on weekdays and weekends.

Five trip modes are included: driving, biking, walking, carpool (trips made by several passengers in an auto vehicle), and microtransit. No trips are classified as public transit, as Arlington does not have a fixed-route public transit system. On the weekday, the mode shares of synthetic trips are as follows: driving accounts for 63.55%, biking for 0.85%, walking for 8.64%, carpooling for 26.48%, and microtransit for 0.48%. On the weekend, the mode shares of synthetic trips are as follows: driving accounts for 67.50%, biking for 0.43%, walking for 6.11%, carpooling for 25.59%, and microtransit for 0.36%.

Microtransit service data for May 2023 are provided by [City of Arlington \(CoA\)](#), which align well with Replica’s synthetic data for the corresponding time period. Due to data privacy concerns, only aggregated values are available, including the total number of monthly and weekly subscribers, as well as the average microtransit in-vehicle time, waiting time, and utilization rate (measured as the number of served passengers per vehicle per hour). We use the average service performance to calibrate our microtransit simulator and the total number of subscribers to estimate the upper-branch model.

4.1.2. Microtransit simulator calibration

We employ a grid search with predefined searching ranges and intervals to calibrate parameters in NOMAD-RPS, ensuring that the simulation results closely align with the average service

performance provided by CoA. The calibration process focuses on several parameters mentioned in [Section 3.2.1](#).

- The number of vehicles in operation is calibrated within a range of 40 to 80, with an interval of 5, and the final values set at 55 for weekdays and 35 for weekends.
- The maximum passenger walking time is explored within a range of 10 to 20 minutes, with an interval of 2 minutes, and the final value set at 12 minutes for both weekdays and weekends.
- The maximum passenger waiting time is tuned between 30 and 60 minutes, with an interval of 10 minutes, and the final value set at 40 minutes for both weekdays and weekends.
- The weight assigned to operating cost (Theta) is calibrated between 0 and 1, with an interval of 0.1, and the final value set at 0.2 for both weekdays and weekends.
- The forward-looking parameter (Beta) is calibrated between 0 and 1, with an interval of 0.1, and the final values set at 0.2 for weekdays and 0.1 for weekends.

To accelerate the simulation for the entire city, we aggregate trip origins and destinations to their respective block group centroids and use the links between these centroids to construct the network, resulting in a computing time of approximately one minute per simulation round. [Table 2](#) presents a comparison between simulation results and the data from CoA. The simulated average in-vehicle travel time is slightly longer than the observed values, while the simulated utilization rate is slightly lower. The largest percentage difference is approximately 15%.

Table 2

A comparison between simulation results and ground truth data.

	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	--

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

4.1.3. Model specification

In the upper branch, the prices of weekly and monthly ride passes are set at \$25 per week and \$80 per month, in accordance with Via Arlington’s current subscription pricing policy. Marginal subscription data from CoA shows that in May 2023, there were 412 active subscribers, accounting for 0.14% of the total residents (0.29 million) who had at least one synthetic trip. Among these subscribers, 320 opted for the weekly ride pass, while 92 subscribed to the monthly ride pass. Since we are building the choice model using the total population from the synthetic data, we can directly set $Num_{weekly} = 320$ and $Num_{monthly} = 92$ in [Eq. \(19\)](#) to estimate subscription choice parameters. The safety margin b is set equal to the 75th percentile. The [Algorithm 2](#) tolerance is set to an average percentage change of 0.1% in the parameters.

In the lower branch, since Replica’s synthetic trip data combines microtransit in-vehicle and waiting time, we obtain $WT_{MT,t}$ and $TT_{MT,t}$ from the calibrated simulator based on observed microtransit demand. The utility functions of the five modes are defined in [Eqs. \(36\) – \(40\)](#).

$$V_{n,driving,t} = \beta_{auto_tt,n} TT_{driving,t} + \beta_{cost,n} COST_{driving,t} + asc_{driving,t}, \quad \forall n \in N, t \in T \quad (36)$$

$$V_{n,biking,t} = \beta_{non_auto_tt,n} TT_{biking,t} + asc_{biking,t}, \quad \forall n \in N, t \in T \quad (37)$$

$$V_{n,walking,t} = \beta_{non_auto_tt,n} TT_{walking,t} + asc_{walking,t}, \quad \forall n \in N, t \in T \quad (38)$$

$$V_{n,carpool,t} = \beta_{auto_tt,n} TT_{carpool,t} + \beta_{cost,n} COST_{driving,t}, \quad \forall n \in N, t \in T \quad (39)$$

$$\begin{aligned} V_{n,MT,t|s} = & \beta_{auto_tt,n} TT_{MT,t} + \beta_{wt,n} WT_{MT,t} + Y_{n,none} \beta_{cost,n} COST_{n,MT,t} \\ & + \beta_{shopping} SH_{n,t} + \beta_{school} SC_{n,t} + \beta_{other} OT_{n,t} \\ & + \beta_{commute} COM_{n,t} + \beta_{noncom} NCOM_{n,t} + asc_{MT,t}, \end{aligned} \quad \forall n \in N, t \in T \quad (40)$$

where $\beta_{auto_tt,n}$, $\beta_{non_auto_tt,n}$ are parameters of auto and non-auto travel time. TT_* , $COST_*$, and asc_* present the travel time, travel cost, and mode-specific constants for these modes. Carpool is set as the reference level. $SH_{n,t}$ is a dummy variable indicating whether the trip is for shopping, $SC_{n,t}$ is a dummy variable indicating whether the trip is to school, and $OT_{n,t}$ is a dummy variable indicating whether the trip serves other purposes. $COM_{n,t}$ is a dummy variable indicating whether the trip is part of a commute tour, and $NCOM_{n,t}$ is a dummy variable indicating whether the trip is part of a non-commute tour.

One of the enduring challenges in building a RP choice dataset is that only the attributes of the chosen mode are available, i.e., if an individual has an observed driving trip, we need to infer the travel time and cost of microtransit or biking for that trip. Using large-scale synthetic trip data can address this challenge, as for each origin-destination (OD) pair, we have a sufficient number of trips using different modes. In that case, missing mode attributes in a trip can be obtained by averaging mode attributes from other observations along the same OD pair. Since microtransit trips account for only a small proportion, we infer $WT_{MT,t}$ and $TT_{MT,t}$ for non-microtransit users by averaging the corresponding values from microtransit users. The attributes are summarized in [Table 3](#).

Table 3
Summary of mode attributes in the lower branch.

Attribute	Notation	Weekday			Weekend		
		Mean	Std.	50%	Mean	Std.	50%
Driving travel time (min)	$TT_{driving,t}$	12.52	6.87	11.11	12.51	6.77	11.12
Driving travel cost (\$)	$COST_{driving,t}$	0.31	0.25	0.23	0.32	0.25	0.24
Biking travel time (min)	$TT_{biking,t}$	17.86	11.19	15.90	17.96	11.07	16.00
Walking travel time (min)	$TT_{walking,t}$	40.98	25.13	38.75	41.07	24.83	39.05
Carpool travel time (min)	$TT_{carpool,t}$	12.64	7.24	11.00	12.62	7.11	11.04
Carpool travel cost (\$)	$COST_{carpool,t}$	0.16	0.12	0.12	0.16	0.12	0.12
Microtransit in-vehicle time (min)	$TT_{MT,t}$	12.59	6.80	11.19	12.58	6.70	11.21
Microtransit waiting time (min)	$WT_{MT,t}$	14.12	0.38	14.11	11.71	0.40	11.71
Microtransit trip fare (\$)	$COST_{MT,t}$	3.82	0.71	3.50	3.84	0.71	3.50
Trip purpose = shopping	$SH_{n,t}$	0.17	0.38	0	0.27	0.42	0
Trip purpose = school	$SC_{n,t}$	0.20	0.61	0	0.02	0.10	0
Trip purpose = other	$OT_{n,t}$	0.64	0.48	1	0.71	0.46	1

Tour type = commute	$COM_{n,t}$	0.45	0.50	0	0.13	0.34	0
Tour type = non-commute	$NCOM_{n,t}$	0.55	0.52	1	0.87	0.36	1

Note: The unit of time is transformed to hours when estimating the model.

4.1.4. Scenario Design

Based on the behavior model and simulation framework, we focus on two key revenue management scenarios, each addressing different aspects of pricing and subsidy strategies in the microtransit system.

In the ride pass pricing policy scenario, we aim to determine the optimal combination of weekly and monthly ride pass prices that maximizes total daily revenue. We explore how different pricing structures influence ridership levels and overall revenue generation, which is particularly relevant for optimizing subscription models, encouraging ridership, and enhancing the financial sustainability of the microtransit service. According to the current pricing policy, we set the range of weekly price to [\$10, \$40] and the range of monthly price to [\$40, \$100], each of them divided into 20 intervals, resulting in $20 \times 20 = 400$ pricing scenarios as inputs of our simulation framework. Metrics defined in Section 3.3.3 are used for evaluation.

In the event- or place-based subsidy scenario, we assess the impact of targeted discounts on microtransit trips linked to specific locations or events. These include essential infrastructure such as hospitals, where improved access can enhance healthcare equity, and high-traffic events like football games, where strategic subsidies could help mitigate congestion and reduce reliance on private vehicles. For the event-based subsidy, we focus on the events at AT&T Stadium, which is home of the Dallas Cowboys. For the place-based subsidy, we focus on Medical City Arlington, a major local healthcare facility. Three discounting scenarios are considered in our simulation: no discount, 50% discount, and 100% discount. For each scenario, we quantify the reduction in private car usage and estimate the additional subsidy required to maintain the affordability of these discounted fares.

4.2. Model results

This section presents the results of our behavior model. The experiments were conducted on a local machine equipped with an Intel Core i7-10875H CPU and 32GB of RAM. Optimization problems were solved using the Gurobi package in Python. [Algorithm 2](#) took 17.15 hours and 3 iterations to converge for the nested model, with AMXL estimation in the lower branch accounting for the majority of the computing time. [Algorithm 1](#) took 9.08 hours and 28 iterations to converge using weekday data containing 699,995 trips and 7.95 hours and 24 iterations to converge using weekend data containing 646,784 trips. Standard errors of the taste parameters are computed via bootstrapping with 30 resamples ([Krueger et al., 2023](#)). We present the model results from three aspects: (1) basic statistics; (2) taste parameter distribution; and (3) CS and elasticity estimates.

4.2.1. Basic statistics

[Table 4](#) summarizes the values, standards error, and significant levels of parameters in the upper-branch subscription choice model. All the estimated parameters are significant, and their signs align with our empirical expectations: (1) The positive parameters for benefits gained on weekdays (β_{gain}^{we}) and weekends (β_{gain}^{wd}) confirm that increased utility from microtransit usage encourages

ride pass subscription; (2) The strong positive parameter for previous microtransit users ($\beta_{MT-user}$) reinforces the notion that prior usage significantly influences subscription likelihood; and (3) The negative constants for weekly (asc_{weekly}) and monthly ($asc_{monthly}$) passes reflect the low subscription rate (only 0.14% of the residents are subscribers), as Arlington Via has not yet been widely adopted.

Table 4
Results of the upper-branch subscription choice model

Parameters	Mean	Std. Error	t-stat.
Ride pass price/trip cost ratio (f_{rp})	0.478	0.037	12.92***
Benefits gained on weekdays (β_{gain}^{we})	3.156	0.422	7.48***
Benefits gained on weekends (β_{gain}^{wd})	1.505	0.143	10.52***
Previous microtransit user ($\beta_{MT-user}$)	4.767	0.098	48.64***
Constant for weekly pass (asc_{weekly})	-0.844	0.128	-6.59***
Constant for monthly pass ($asc_{monthly}$)	-1.186	0.166	-7.14***
Total number of residents: 293,663			
Observed weekly pass subscribers: 320	Predicted monthly pass subscribers: 320		
Observed monthly pass subscribers: 92	Predicted monthly pass subscribers: 93		

The subscription model demonstrates high predictive accuracy. The predicted number of weekly pass subscribers (320) and monthly pass subscribers (93) closely match the observed values. Table 5 presents predicted number of subscribers across different demographic segments, which is unavailable without the estimated model. The not-low-income segment constitutes the majority of subscribers, accounting for 58.60% of the total. The student segment emerges as the second-largest subscriber group, comprising 28.81% of total subscribers. In contrast, the low-income segment exhibits a substantially lower subscription rate, representing only 2.42% of total subscribers, potentially due to financial constraints or limited service accessibility.

Table 5
Predicted ride pass ownership by demographic segments

	Weekly RP subscribers	Monthly RP subscribers	Total subscribers
Non-low-income segment	188 (45.52%)	54 (13.08%)	242 (58.60%)
Low-income segment	8 (1.94%)	2 (0.48%)	10 (2.42%)
Senior segment	32 (7.75%)	10 (2.42%)	42 (10.17%)
Student segment	92 (22.28%)	27 (6.54%)	119 (28.81%)
Total population	320 (77.48%)	93 (22.52%)	413 (100%)

Note: Each entry represents the number of subscribers, and the number in the parenthesis is the proportion.

Table 6 summarizes the mean values, standards error, and significant levels of parameters in the mode choice model for both weekday and weekend trips. All the estimated parameters are significant at 1% level. The models demonstrate a strong goodness-of-fit, as reflected by the McFadden R-square values (0.603 for weekdays and 0.576 for weekends). The mode-specific constants reveal a strong preference for private vehicle use in the study area, with a significantly positive constant for driving (1.433 on weekdays and 1.636 on weekends). In contrast, microtransit exhibits relatively low attractiveness as a travel mode, as evidenced by its negative mode-specific constant (-0.105 on weekdays and -0.121 on weekends) and negative interaction terms with various trip purposes and tour types. Additionally, a comparison between weekday and weekend models

reveals that residents' sensitivity to mode attributes varies slightly across different days of the week. The relatively lower McFadden R-square in the weekend model suggests that travelers exhibit greater flexibility in their mode choices on weekends.

Table 6
Results of the lower-branch mode choice model

Parameters	Weekday			Weekend		
	Mean	Std. Error	T-stat.	Mean	Std. Error	T-stat.
Travel time and cost						
Auto travel time ($\beta_{tt_auto,n}$)	-0.090	0.001	-67.80***	-0.081	0.001	-69.26***
Non-auto travel time ($\beta_{tt_non_auto,n}$)	-0.135	0.001	-119.59***	-0.127	0.001	-121.03***
Microtransit waiting time ($\beta_{wt,n}$)	-0.161	0.002	-106.62***	-0.161	0.001	-132.82***
Travel cost ($\beta_{cost,n}$)	-0.333	0.004	-91.16***	-0.307	0.003	-93.47***
Mode specific constants						
Microtransit constant ($asc_{MT,t}$)	-0.105	0.001	-85.97***	-0.121	0.002	-78.39***
Driving constant ($asc_{driving,t}$)	1.433	0.037	39.03***	1.636	0.032	51.79***
Biking constant ($asc_{biking,t}$)	-0.712	0.005	-131.06***	-0.608	0.005	-117.29***
Walking constant ($asc_{walking,t}$)	0.176	0.009	20.39***	0.125	0.008	16.34***
Trip purpose and tour type						
Trip purpose: shopping ($\beta_{shopping}$)	-0.012	0.000	-47.85***	-0.026	0.000	-98.85***
Trip purpose: school (β_{school})	-0.035	0.000	-134.37***	-0.003	0.000	-10.80***
Trip purpose: other (β_{other})	-0.043	0.000	-164.12***	-0.065	0.000	-248.39***
Tour type: commute ($\beta_{commute}$)	-0.038	0.000	-147.46***	-0.017	0.000	-63.94***
Tour type: non-commute (β_{noncom})	-0.019	0.000	-71.42***	-0.103	0.000	-396.01***
Meta information						
# Observations	699,995 observations			646,784 observations		
Loglikelihood value (null)	-1,126,598			1,040,958		
Loglikelihood value (model)	-447,259			-441,366		
McFadden R-square	0.603			0.576		

Significant levels (p-value): <0.01 '***' <0.05 '**' <0.1 '*'

Since travel time and cost parameters vary across individuals, we can further explore the value-of-time (VOT) of four population segments. The value of in-vehicle time is calculated by dividing the mean value of the auto travel time parameter ($\beta_{tt_auto,n}$) by the mean value of the travel cost parameter ($\beta_{cost,n}$). The value of waiting time is calculated by dividing the mean value of the microtransit waiting time parameter ($\beta_{wt,n}$) by the mean value of the travel cost parameter ($\beta_{cost,n}$). Table 7 lists the VOT by segments calculated using the weekday and weekend models. In general, the VOT on weekdays is higher than on weekends, and the value of microtransit waiting time is higher than in-vehicle time. Among the population segments, the non-low-income segment has the highest VOT while the low-income segment has the lowest VOT. These align with the findings in existing mode choice studies (Fournier & Christofa, 2021; Kolarova et al., 2018).

Table 7
Value of microtransit in-vehicle time and waiting time by demographic segments

	Value of in-vehicle time (\$/hour)		Value of waiting time (\$/hour)	
	Weekday	Weekend	Weekday	Weekend
Non-low-income segment	17.36	15.22	28.61	25.98
Low-income segment	10.24	11.09	16.07	18.07

Senior segment	11.62	10.61	19.87	18.88
Student segment	14.10	11.10	22.47	18.19

4.2.2. Distribution of taste parameters

In our mode choice model, time and cost parameters vary across individuals, mode specific constants vary across trips, and interaction term parameters are homogeneous across all observations. Fig. 4 shows the statistical distribution of mode choice parameters, revealing them to be neither Gaussian nor other parametric distributions. Instead, these parameters can be divided into three categories: (1) evenly-distributed parameters, such as travel cost (B_COST) and driving constant (ASC_DRIVING). These parameters have larger variations, reflecting heterogeneous tastes across agents; (2) highly-concentrated parameters, such as microtransit constant (ASC_MICRO) and non-auto travel time (B_NON_AUTO_TT). These parameters are concentrated around their mean values with small variations, reflecting homogeneous tastes across agents; and (3) parameters following asymmetric (or log-normal) distributions, such as biking (ASC_BIKING) and walking (ASC_WALKING) constants. These parameters exhibit a peak value and a long tail in their distributions, indicating a small proportion of agents being more sensitive to an attribute compared to the majority. Additionally, although the parameters for trip purpose and tour type are assumed to be fixed, they exhibit greater differences between weekdays (Panel (c)) and weekends (Panel (f)) compared to other parameters.

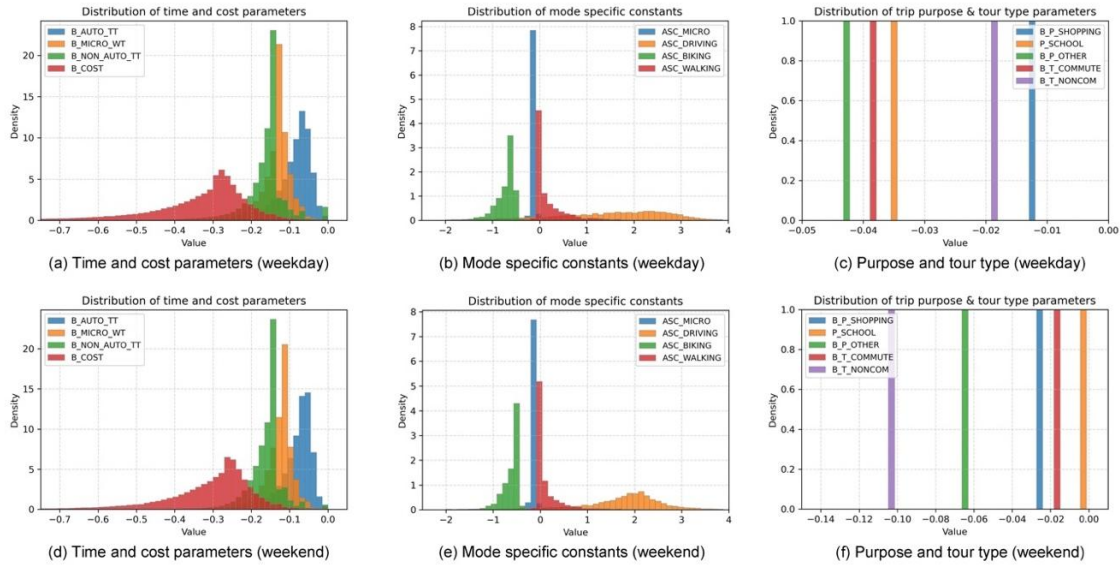


Fig. 4. Statistical distributions of mode choice parameters

Fig. 5 presents the spatial distribution of constants for driving, walking, and microtransit, alongside Arlington's zoning districts (City of Arlington, 2022). Driving constants are generally higher along major roadways and corridors, suggesting a strong preference for driving in well-connected areas. Walking constants exhibit localized variations, with higher values concentrated in denser urban areas, likely reflecting pedestrian-friendly environment. Microtransit constants are generally lower and even-distributed, probably because microtransit is not widely adopted. The spatial distribution of these constants aligns with land use patterns in Panel (g), where commercial

and mixed-use areas support higher walking activity, while lower-density residential zones are more car-dependent. The results highlight the capability of our mode choice models in capturing the influence of the built environment on user preferences.

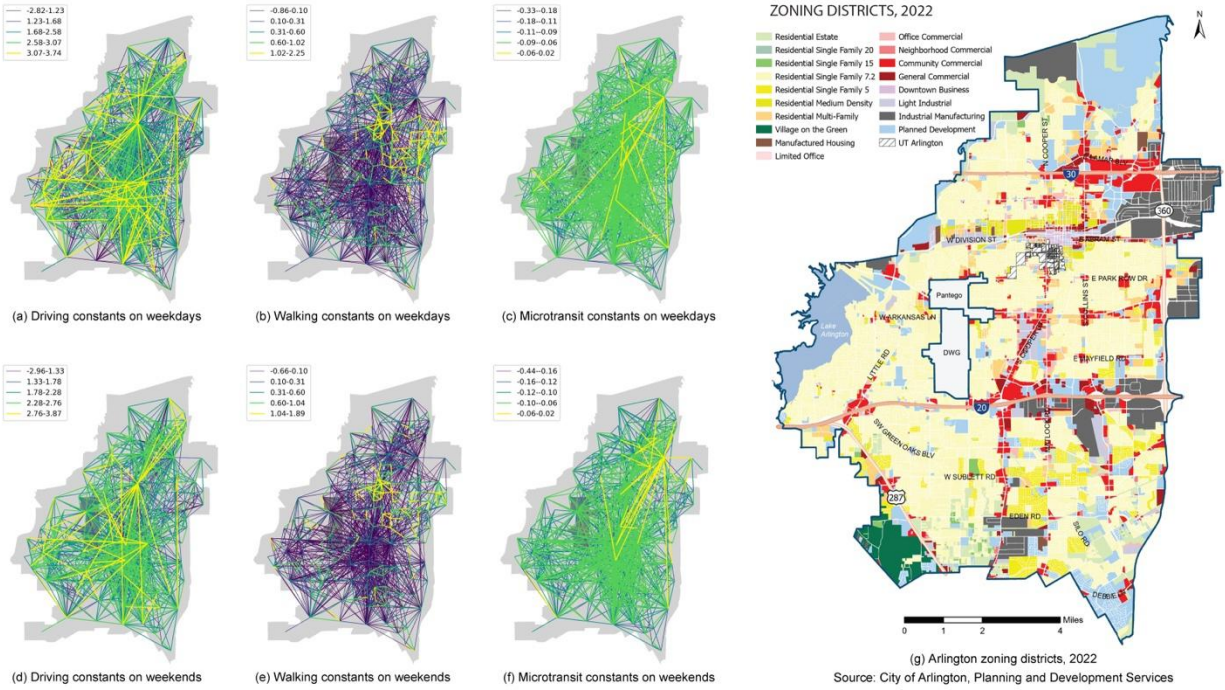


Fig. 5. Spatial distributions of mode specific constants

4.2.3. Consumer surplus and elasticity estimates

Fig. 6 illustrates the distribution of subscription-based and trip-level compensating variation (CV) across four population segments, highlighting differences in how they value ride pass plans and the microtransit service. Panel (a) depicts the CV for having both weekly and monthly ride pass options, ranging from approximately \$0 to \$0.20/week. Notably, the not-low-income segment exhibits the highest values, with a distribution peak around \$0.03/week. In contrast, the senior and low-income segments show relatively lower CV values, with most values concentrated near \$0.01/week. The relatively low value is probably because microtransit occupies such a small mode share.

Panels (b) and (c) compare microtransit CV on weekdays and weekends. In general, weekday CV distributions exhibit greater dispersion across individuals and segments, implying more diverse attitudes toward microtransit on weekdays compared to weekends. The density functions indicate that the low-income and senior segments have the most concentrated peaks near \$0.01/week, suggesting that these groups experience relatively consistent but modest perceived value. The not-low-income segment shows a broader spread, with peaks occurring at slightly higher values, implying higher perceived value and a wider range of user experiences.

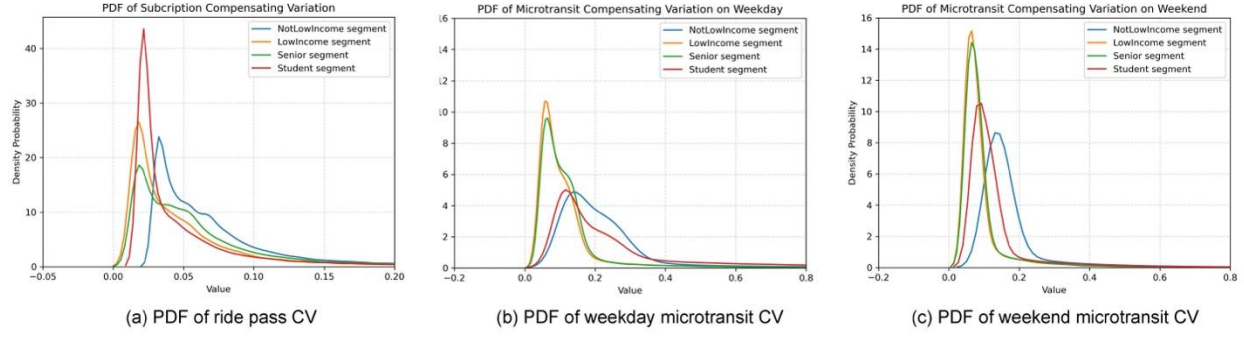


Fig. 6. Probability distribution functions (PDF) of compensating variation (CV) by population segments

Fig. 7 presents the cumulative distribution functions (CDFs) of ride pass elasticity with respect to microtransit service performance on weekdays (Panel (a)) and weekends (Panel (b)). The results reveal that elasticities are consistently negative, indicating that improvements in microtransit service performance increase the likelihood of ride pass subscription. However, the magnitude of elasticity is relatively small, indicating that the relationship between ride pass ownership and service performance falls within the inelastic region, likely due to the small proportion of microtransit users at this stage. Furthermore, elasticity values are more negative on weekdays than on weekends and more negative with respect to waiting time than in-vehicle time, suggesting that quicker service responses during weekdays have a stronger impact on ride pass subscription. These interpretable results not only validate the value of our nonparametric estimation but also provide valuable insights for designing targeted pricing and subsidy strategies.

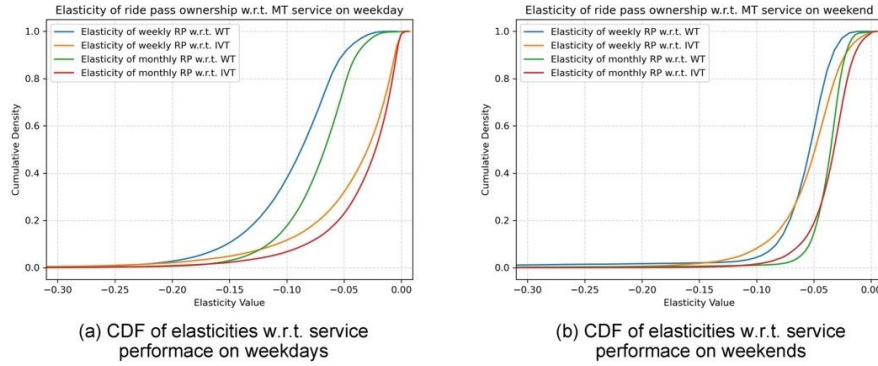


Fig. 7. Cumulative distribution function (CDF) of ridepass ownership elasticity w.r.t. microtransit service performance

4.3. Revenue management policy evaluation

This section demonstrates how our estimated model can be integrated into a simulation-based framework to support revenue management policy evaluation. The simulations were conducted on a local machine equipped with an Intel Core i7-10875H CPU and 32GB of RAM, with computing times per simulation ranging from 1 to 3 minutes.

4.3.1. Ridepass pricing policy

We evaluate the impact of adjusting ride pass prices on total daily revenue by simulating 400 pricing scenarios. Fig. 8 presents how total daily revenue, number of subscribers, and microtransit ridership change based on weekly and monthly ride pass prices. The results show that the optimal pricing strategy to maximize total daily revenue is to reduce the weekly ride pass price from \$25 to \$18.9 and the monthly ride pass price from \$80 to \$71.5. This pricing adjustment leads to an increase in total daily revenue to from \$119,56 per day to \$120,83 per day. Panel (b)-(c) further show why the total revenue increase with the decrease of ride pass price. The revenue growth can be attributed to a higher number of subscribers (635 compared to 413 at the current pricing) and an increase in total microtransit ridership (3,225 trips compared to 3,105 trips). Lowering the price makes the ride pass more attractive to potential subscribers, expanding the customer base and boosting overall ridership, which in turn compensates for the reduced per-pass price and results in higher total revenue.

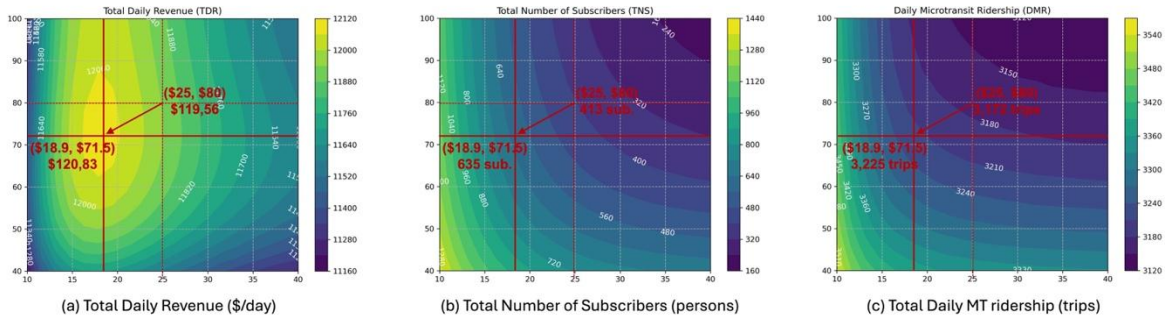


Fig. 8. Contour plots of total daily revenue (a), number of subscribers (b), and microtransit ridership (c) as a function of ride pass prices

4.3.2. Event-based subsidy policy for AT&T Stadium

For the event-based subsidy policy, we focus on the impact of fare discounts on microtransit trips to and from AT&T Stadium, home of the Dallas Cowboys (Fig. 9). The analysis focuses on peak hours from 4 p.m. to 8 p.m. on weekends, coinciding with major sporting events.

The simulation results indicate that implementing a 100% fare discount for trips starting from or ending at AT&T Stadium leads to an increase in microtransit ridership from 78 to 141 trips per event. This increase helps shift some trips away from private vehicle usage, reducing the number of driving trips from 2,207 trips per event to 2,146 trips per event, which corresponds to a reduction of 61 car trips during peak periods. Additionally, the CS per trip increases by \$0.018 due to the fare discount, translating into a total monetary value of $\$0.018 \times 3,559 = \64.62 across all affected trips. However, this policy would require a subsidy of \$533 per event to compensate the revenue loss. A 50% fare discount yields a more moderate impact, increasing microtransit ridership to 97 trips per event, reducing 18 car trips during peak period, while requiring a lower subsidy of \$193 per event. Although the simulated policy impact is relatively small compared to the total trip volume (largely due to the currently low mode share of microtransit), our model and simulation framework provide a quantitative measurement tool for evaluating such policies

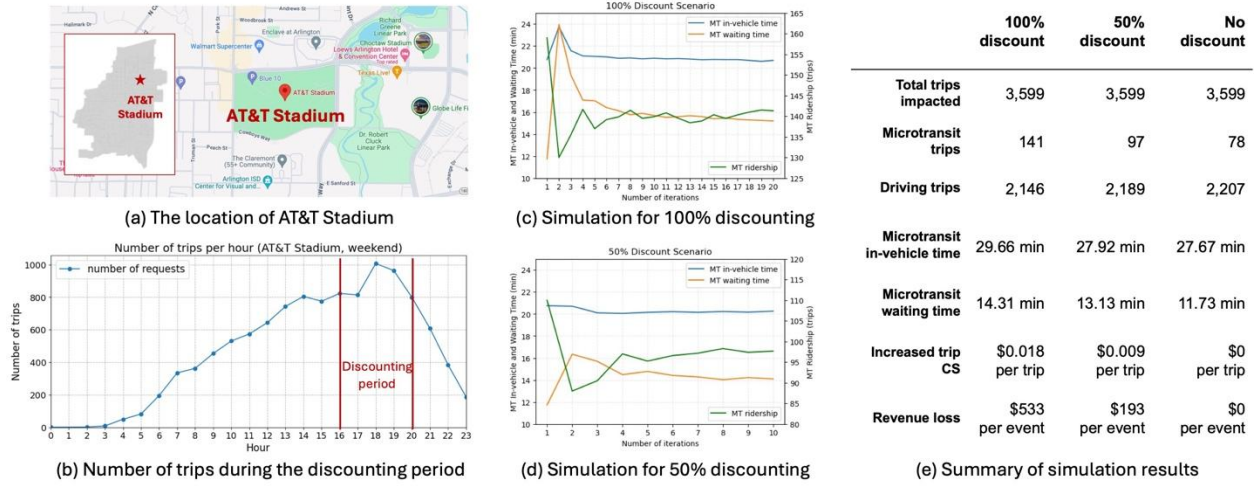


Fig. 9. A summary of two discounting scenarios for trips to AT&T stadium

4.3.3. Place-based subsidy policy for Medical City Arlington

For the place-based subsidy policy, we analyze the impact of fare discounts on microtransit trips to and from Medical City Arlington, a key healthcare facility in the region (Fig. 10). The analysis focuses on weekdays, particularly during the discounting period from 6 a.m. to 9 p.m., when a significant number of trips are made to the medical center. The goal of this policy is to improve access to healthcare facilities by encouraging microtransit usage through fare reductions.

The simulation results indicate that implementing a 100% fare discount for trips starting from or ending at Medical City Arlington increases microtransit ridership from 42 to 124 trips per day, leading to a reduction in driving trips from 3,340 to 3,263, which corresponds to 77 fewer car trips during peak periods. Additionally, the CS per trip increases by \$0.025, translating into a total monetary value of $\$0.025 \times 6,322 = \158.05 across all affected trips. However, this policy would require a subsidy of \$483 per day to compensate for the revenue loss. A 50% fare discount yields a more moderate impact, increasing microtransit ridership to 67 trips per day, reducing 24 car trips, while requiring a lower subsidy of \$145 per day.

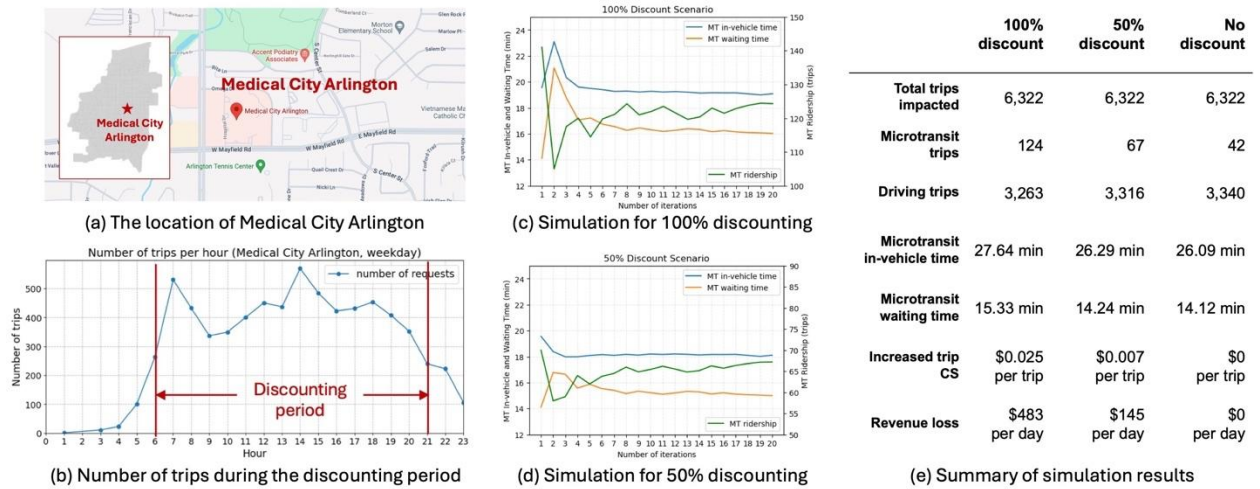


Fig. 10. A summary of two discounting scenarios for trips to Medical City Arlington

5. Conclusion

As microtransit services continue to evolve, understanding their adoption and revenue management remains a critical challenge. This study introduces a nested nonparametric logit model that jointly estimates travel mode and ride pass subscription choices using a combination of marginal subscription and synthetic population data. By leveraging agent-based estimation, the model captures heterogeneous user preferences while maintaining theoretical consistency with discrete choice modeling. Our choice-based simulation framework further extends this capability, enabling policymakers to assess pricing and subsidy policies with quantitative precision.

The methodological contributions of this work are threefold. First, the integration of synthetic population data (1.35 million trips made by 0.4 million Arlington residents) enables citywide demand estimation with spatiotemporal granularity, overcoming the limitations of small-sample SP surveys. Second, the agent-based mixed logit (AMXL) approach captures individualized preferences without restrictive parametric assumptions, revealing asymmetric and multimodal distributions of taste parameters that conventional mixed logit models fail to represent as well as achieving high McFadden R^2 values (0.603 for the weekday model and 0.576 for the weekend model). Third, the nested structure bridges subscription and mode choice dynamics, enabling operators to quantify subscriber distribution across demographic segments, with 58.60% from the not-low-income segment, 2.42% from the low-income segment, 10.17% from the senior segment, and 28.81% from the student segment.

The policy evaluation highlights key insights into microtransit pricing and subsidy strategies. Our simulation results suggest that lowering ride pass prices—from \$25 to \$18.9 for weekly passes and \$80 to \$71.5 for monthly passes—can increase total revenue by \$127 per day by attracting more subscribers and riders. Additionally, 100% fare discounts at AT&T Stadium and Medical City Arlington can encourage microtransit use, reducing 61 and 82 car trips, respectively, but require subsidies of \$533 per event and \$483 per day. Although the overall impact on total trip volume remains modest due to microtransit's currently low mode share, these results illustrate how pricing and subsidy interventions can influence ridership and financial sustainability.

There are several promising directions for future research. While this study focuses on static pricing policies, integrating dynamic fare adjustments based on demand fluctuations could further enhance revenue management. Moreover, extending the model to multi-modal networks and incorporating service-level optimization could provide deeper insights into microtransit's role in urban mobility. Lastly, computational efficiency remains an area for improvement—parallel computing could accelerate estimation and make the approach more scalable. By refining these aspects, the proposed framework can be applied to a wider range of cities and transit systems, supporting more data-driven decision-making in microtransit planning and operations.

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CRedit authorship contribution statement

The authors confirm contribution to the paper as follows: study conception and design: Joseph Y. J. Chow, Xiyuan Ren, Venkatesh Pandey; data collection: Joseph Y. J. Chow, Xiyuan Ren; analysis and interpretation of results: Xiyuan Ren, Joseph Y. J. Chow, Linfei Yuan; draft manuscript preparation: Xiyuan Ren, Joseph Y. J. Chow, Venkatesh Pandey. All authors reviewed the results and approved the final version of the manuscript.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT 4o in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Declaration of competing interest

The authors declare no competing interests.

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