Modeling Day-to-Day Modes Choices with Heterogeneous Travelers under MaaS Scenarios

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SHORT SUMMARY

MaaS (Mobility as a Service) platforms allow travelers to choose from various mode combinations, altering their behaviors and decision-making. This paper introduces a dynamic mode choice evolution model for heterogeneous users, focusing on long-term learning. The model adjusts choices based on personal experience and historical data, incorporating a value of time (VOT) function to distinguish between car and non-car owners. Based on Beijing's MaaS scenario, results indicate that learning from past experiences accelerates convergence, with the learning parameter affecting the rate but not the final equilibrium. The impact of transfer times for combined modes on mode choices for both car and non-car owners is analyzed. Non-car owners are less sensitive to VOT in their choices, while car owners show more heterogeneity in their behaviors. Therefore, providing uniform incentives for non-car owners can promote public transport, while differentiated VOT-based pricing for car owners can reduce private car use.

Keywords: MaaS, dynamic mode choice, heterogeneous users, long-term learning behaviors

1. INTRODUCTION

Traffic flow in transportation networks is not always in a steady state. Passengers continuously adjust their travel mode and/or route based on real-time conditions, which has spurred interest in the dynamics and evolution of transportation systems. Most existing day-to-day studies focus on dynamic behaviors under single-mode (Yang and Zhang, 2009; Guo et al., 2013; Smith and Watling, 2016) or dual-mode models (Cantarella et al., 2015; Li and Yang, 2016; Li et al., 2018; Liu and Szeto, 2020), with some exploring the parking-for-transfer problem (Liu and Geroliminis, 2017).

Mobility as a Service (MaaS) integrates various travel modes into a single digital platform. Travelers can easily choose from combinations like bus + subway or taxi + subway. For example, Beijing's MaaS platform (see Fig. 1) enhances navigation APP with intelligent travel features, offering direct comparisons of multiple travel modes and combinations, greatly improving travel flexibility and convenience (Zhang and Xu, 2025). This paper investigates the introduction of combined mode choice in the MaaS scenario, examining how users dynamically adjust their travel modes based on optimal route guidance, while excluding route choice from the analysis. The model extends traditional single-mode choice to multiple transportation modes, assuming the MaaS platform provides the optimal route, simplifying decision-making and enhancing flexibility. Users of MaaS platforms include car owners and non-car owners. This paper considers the heterogeneity of these user types and incorporates the value of time (VOT) function to represent these differences. These differences affect mode choice and traffic flow.

In actual travel, users’ mode choices are influenced not only by their experience of the last day but also by experiences over a long period of time. Most existing studies focus on short-term learning models (e.g., yesterday’s experience) to simulate decision updates (Ye et al., 2021; Li et al., 2018). This paper introduces long-term learning behavior and uses a learning decay model to represent how user experience decays over time, revealing its impact on travel mode choices in MaaS scenarios and its role in the dynamic evolution of transportation systems.

Thus, this paper proposes a dynamic mode evolution model for heterogeneous users considering long-term learning. In the experiment, we also consider the impact of transfer times for different combined modes on mode choices of different user types in the MaaS scenario. This comprehensive model provides insights into the role of MaaS platforms in promoting behavior change and MaaS system optimization.

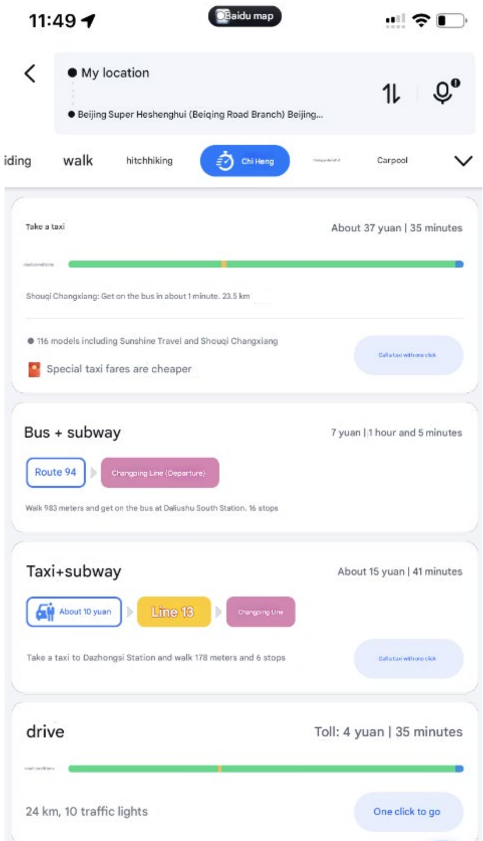


Figure 1: Travel mode recommendation interface of MaaS 2.0 platform

2. METHODOLOGY

2.1 Problem description

This paper examines the mode evolution process of heterogeneous users in a MaaS scenario, based on travel mode recommendations from Beijing’s MaaS platform. We assume users commute between residential and work areas, selecting travel modes through the MaaS platform, with the same origin and destination. Various travel mode combinations are considered to meet urban travel needs (see Fig. 2). Commuters travel from home (O) to work (D) with the option to transfer at station T (e.g., from subway to bus or ride-hailing). The shared road network includes private cars (C) and ride-hailing vehicles (R), which share the same routes (l_1, l_2).

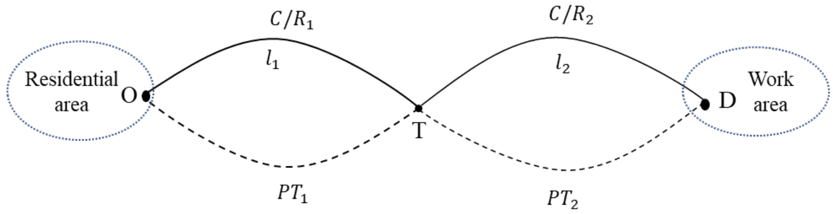


Figure 2: Travel modes in MaaS

We consider two user types: car owners and non-car owners. The available modes for each user type are as follows:

- Non-car owners: three modes ($m \in M^1 = \{R(R_1 + R_2),\ RP(R_1 + PT_2), PT(PT_1 + PT_2)\}$)
- Car owners: four modes ($m \in M^2 = \{R(R_1 + R_2), RPT(R_1 + PT_2), PT(PT_1 + PT_2), \mathrm{C}(C_1 + C_2)\}$)

2.2 Dynamic mode choice evolution model for heterogeneous users

We model the dynamic evolution of travel mode choices based on users' learning from past travel experiences. This study extends existing research on perceived costs (Li et al., 2018) by introducing a long-term learning model for heterogeneous users.

We define two types of users: non-car users (1) and car users (2). The total number of non-car users is N^1, and car users is N^2. The n-th non-car user is denoted as n^1, and the n-th car user is denoted as n^2. The perceived travel cost for the n-th user choosing mode m on day t is denoted as $c_{n,m}^{p,t}$. Similarly, the experienced cost is denoted as $c_{n,m}^{e,t}$. Each user's perceived cost on day t is calculated based on both past perceived and experienced costs.

The long-term learning model uses a decreasing learning rate (ω_i) to reflect how users increasingly rely on recent experiences as they accumulate more travel history. We draw inspiration from Ebbinghaus's forgetting (Finkenbinder, 1913) curve to construct the learning rate decay function ω_i, which represents the user's behavior of learning from historical experiences. ω_i indicates the learning rate, which decreases over time i.

$$\omega_i = k * e^{-\lambda i} \tag{1}$$

Where, k represents the initial learning rate, which reflects the user's reliance on long-term experiences. In this paper, k indicates the weight assigned to the user's cumulative historical experiences. A higher k value (approaching 1) suggests that users are more inclined to make choices based on long-term aggregated perceptions of travel costs, such as those derived from historical modes choice. The parameter λ, known as the decay factor, controls the rate at which weights decrease over time. In the context of travel behavior, λ captures the user's sensitivity to recent travel experiences. A larger λ implies that users place greater emphasis on yesterday's (or other recent) experiences while relying less on earlier historical experiences. A higher k indicates stronger user inertia or stability, representing greater reliance on long-term accumulated experiences. Conversely, a larger λ reflects higher sensitivity to short-term fluctuations, emphasizing the importance of recent experiences over historical trends. Figure 3 is an example diagram of learning rate ω_i, where i represents day.

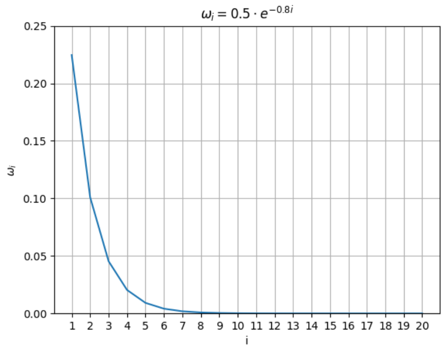


Figure 3: The variation of the learning rate ω_i with respect to the day.

Perceived Cost for Non-Car Users $c_{n^1,m}^{p,t}$:

$$c_{n^1,m}^{p,t} = (1 - \sum_{i=1}^{t-1} \omega_i) c_{n^1,m}^{p,t-1} + \sum_{i=1}^{t-1} \omega_i * c_{n^1,m}^{e,t-i} \tag{2}$$
$$0 < \sum_{i=1}^{t-1} \omega_i < 1, n^1 \in N^1, m \in M^1$$

Perceived Cost for Car Users $c_{n^2,m}^{p,t}$:

$$c_{n^2,m}^{p,t} = (1 - \sum_{i=1}^{t-1} \omega_i) * c_{n^2,m}^{p,t-1} + \sum_{i=1}^{t-1} \omega_i * c_{n^2,m}^{e,t-i} \tag{3}$$
$$0 < \sum_{i=1}^{t-1} \omega_i < 1, n^2 \in N^2, m \in M^2$$

For non-car users n^1 and car users n^2, the experienced travel cost for choosing transportation mode mmm on day t is expressed as:

$$c_{n^1,m}^{e,t} = \alpha_{n^1} * TT_m(x_m^t) + \tau_m^d,\ n^1 \in N^1, m \in M^1 \tag{4}$$
$$c_{n^2,m}^{e,t} = \alpha_{n^2} * TT_m(x_m^t) + \tau_m^d,\ n^2 \in N^2, m \in M^2 \tag{5}$$

Where α_{n^1} and α_{n^2} represent the users' value of time, $TT_m^t(x_m^t)$ denotes the actual travel time of mode m on day t, depending on the day's traffic conditions x_m^t, and τ_m^d signifies the actual travel cost of mode m in period d. The prices within each period d are fixed

User choice behavior is based on perceived utility and the logit model. On each day t, users choose travel modes based on perceived utility, with random terms $\varepsilon_{n,m}^t$ following a Gumbel distribution with mean zero. The perceived utility of mode m on the day t can be defined as:

$$u_{n^1,m}^{p,t} = -c_{n^1,m}^{p,t} + \varepsilon_{n^1,m}^t \quad n^1 \in N^1, m \in M^1 \tag{6}$$
$$u_{n^2,m}^{p,t} = -c_{n^2,m}^{p,t} + \varepsilon_{n^2,m}^t \quad n^2 \in N^2, m \in M^2 \tag{7}$$

The probability of a user choosing each mode is calculated based on the Logit model. Therefore, the probability that user n chooses mode m at time step t is

$$p_{n^1,m}^t = \frac{e^{-\theta c_{n^1,m}^{p,t}}}{\sum_{m' \in M^1} e^{-\theta c_{n^1,m'}^{p,t}}} \tag{8}$$

$$p_{n^2,m}^t = \frac{e^{-\theta c_{n^2,m}^{p,t}}}{\sum_{m' \in M^2} e^{-\theta c_{n^2,m'}^{p,t}}} \tag{9}$$

The total number of users choosing each mode is determined by the sum of probabilities calculated by the Logit model, as shown in the following formula:

$$x_m^t = \sum_{n^1=1}^{N^1} p_{n^1,m}^t + \sum_{n^2=1}^{N^2} p_{n^2,m}^t \tag{10}$$

where $p_{n,m}^t$ is the probability function of choosing mode m, $m \in M$.

3. NUMERICAL EXPERIMENTS

3.1 Travel time and heterogeneity setup

For private car mode:

$$TT_c = t_{1,0}\left(1 + 0.15\left(\frac{x_{l_1}}{H_{l_1}}\right)^4\right) + t_{2,0}\left(1 + 0.15\left(\frac{x_{l_2}}{H_{l_2}}\right)^4\right) \tag{11}$$

For single R mode:

$$TT_r = w_r + t_{1,0}\left(1 + 0.15\left(\frac{x_{l_1}}{H_{l_1}}\right)^4\right) + t_{2,0}\left(1 + 0.15\left(\frac{x_{l_2}}{H_{l_2}}\right)^4\right) \tag{12}$$

$$x_{l_1} = x_r + x_{rpt} \tag{13}$$

$$x_{l_2} = x_r \tag{14}$$

For combine PT mode:

$$TT_{pt} = t_{walk_1} + t_{pt_1} + t_{pt_2} + t_{transfer}^{pt} + t_{walk_2} \tag{15}$$

For combine R+PT mode:

$$TT_{rpt} = w_r + t_{1,0}\left(1 + 0.15\left(\frac{x_{l_1}}{H_{l_1}}\right)^4\right) + t_{pt_2} + t_{transfer}^{rpt} + t_{walk_2} \tag{16}$$

Each vehicle type (car or ride-hailing) is assumed to carry one person only, with no carpooling. w_r represents the waiting time for ride-hailing vehicles, and $t_{1,0}$, $t_{2,0}$ are the free-flow times for Line 1 and Line 2, respectively. H_{l_2} and H_{l_2} are the traffic flow capacities for Lines 1 and 2. t_{pt_1} and t_{pt_2} are fixed times for public transport, while $t_{transfer}$ is the transfer time between services. t_{walk_1} and t_{walk_2} are the walking times to/from the public transport station.

The following Eq. gives the user's time value function (Wu and Huang, 2014).

$$\begin{cases} \alpha_{n^1} = 50 - 30 * \frac{n^1}{N^1}, users\ without\ cars\ n^1 \in N^1 \\ \alpha_{n^2} = 60 - 30 * \frac{n^2}{N^2}, users\ with\ cars\ n^2 \in N^2 \end{cases} \tag{17}$$

Although the VOT function is continuous, each user's VOT is represented as a discrete point ranked in descending order. Car owners typically have a higher VOT than non-car owners.

3.2 Specific parameter settings

We selected a commuting O-D pair in Beijing as a case study, with the characteristics of various travel modes and their corresponding routes shown in Table 1.

Table 1: Specific parameter settings of MaaS Scenario

Parameters	Specifications
N	4000

N^1	0.5N
N^2	0.5N
$t_{1,0}, t_{2,0}, t_{pt}(h)$	0.3, 0.4, 0.55
$H_1, H_2(vechicle/h)$	[1300,1300]
$w_r(h)$	0.1
$t_{walk1} = t_{walk1}$(h)	0.05
t_{pt1}, t_{pt2} (h)	0.7
$t_{transfer}^{pt}$ (h)	0.1
$t_{transfer}^{rpt}$ (h)	0.1/0.2
$\tau_{pt}, \tau_{pt+r}, \tau_c, \tau_r(yuan/CNY)$	8,14,20,50

4. RESULTS AND ANALYSIS

First, we investigate how the equilibrium state of the Dynamic Mode Choice Evolution Model for heterogeneous users, considering long-term learning, is influenced by different learning parameters.

GAP is a criterion for judging convergence, and is calculated as follows:

$$\text{Gap}=\frac{\sqrt{\sum_m (x_m^t - x_m^{t-1})^2}}{\sum_m x_m^{t-1}} \tag{18}$$

4.1 Different learning parameters

4.1.1 Different k ($\lambda = 0.8$)

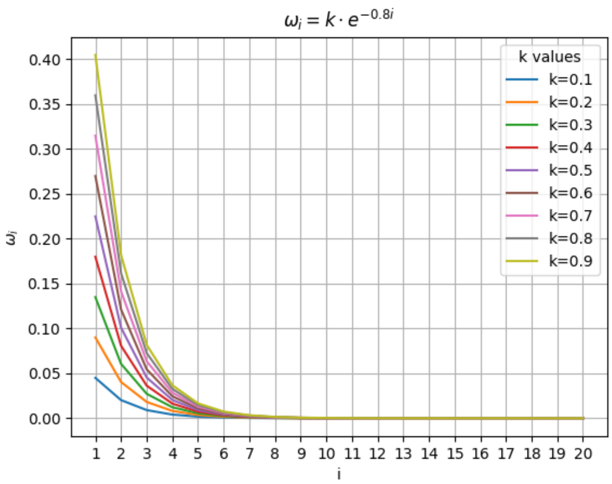
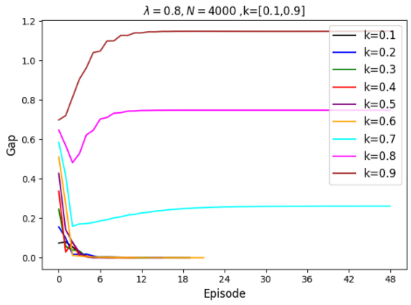
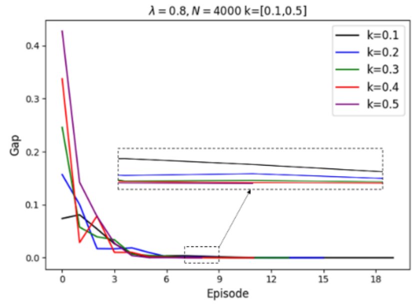


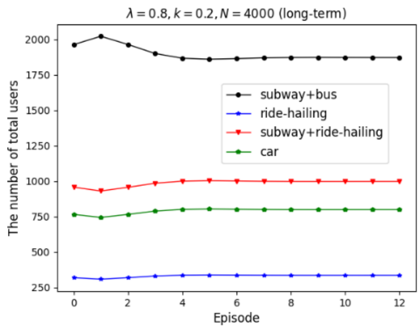
Figure 4: The variation of the learning rate ω_i with different k. k represents the initial learning rate (e.g., reflecting the learning rate from the previous day)

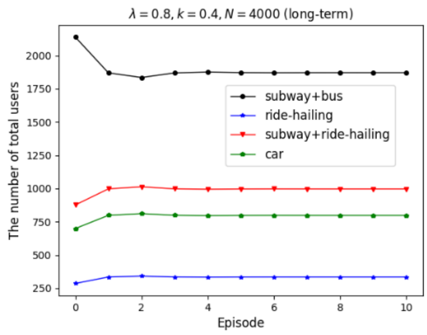




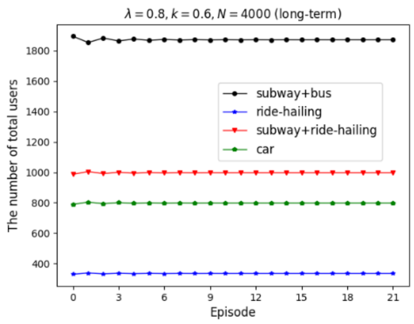
(a) $k =$ [0.1,0.9] (b) $k =$ [0.1,0.5]

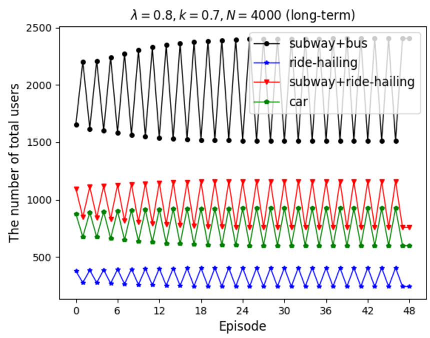
Figure 5: Gap for different values of k





(a) $k = 0.2$ (b) $k = 0.4$





(c) $k = 0.6$ (d) $k = 0.7$

Figure 6: Evolution of user numbers for four modes across different k

Figures 5 and 6 show that the system converges when $k = [0.1, 0.5]$, with faster convergence at higher k values. Within this range, a larger k increases the reliance on past experiences and accelerates convergence. However, when $k = 0.6$, the convergence rate slows down, and for $k > 0.6$, convergence fails. This is due to the system's excessive reliance on past experiences, preventing effective adaptation to new changes. When $\lambda = 0.8$ and $k > 0.6$, $\omega_i = k * e^{-0.8i}$>1, which results in non-convergence. Figures 6(a)-(c) demonstrate that if an equilibrium state exists, it is unique regardless of k or λ values.

4.1.2 Different λ (k=0.5)

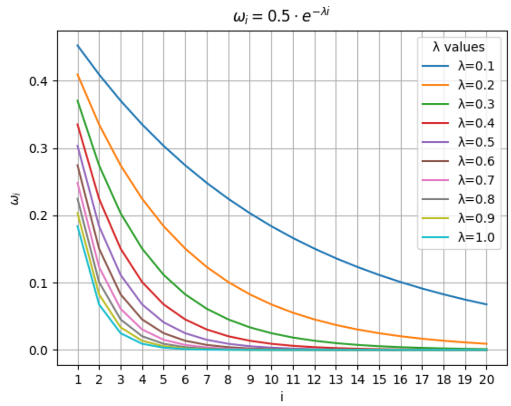
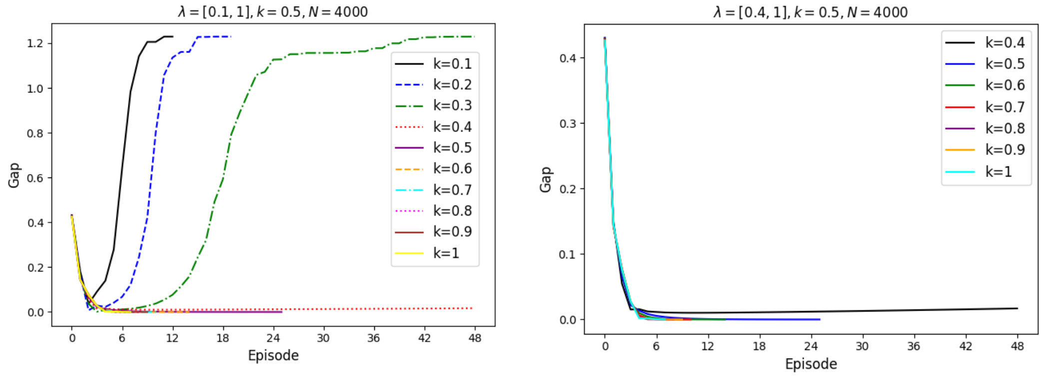


Figure 7: The variation of the learning rate ω_i with different λ. λ acts as the decay factor, controlling how quickly the learning rate decreases over time.



(a) $\lambda\ = [0.1,1]$

(b) $\lambda\ = [0.4,1]$

Figure 8: Gap for different values of λ

Figures 8 shows that the system does not converge when $\lambda\ =\ [0.1, 0.4]$. For $\lambda\ >\ 0.4$, the system converges, with faster convergence as λ increases within the range $[0.5, 1]$. When $k\ =\ 0.5$ and $\lambda\ >\ 0.4$, 0< $\omega_i = 0.5e^{-\lambda i}$<1, so the system fails to converge.

A small λ leads to faster updates, relying more on recent experiences, but also increases sensitivity to short-term fluctuations, hindering convergence. As λ increases, the system converges faster, with a larger decay factor emphasizing long-term experiences, reducing the impact of short-term fluctuations and stabilizing the learning process.

In conclusion, appropriately integrating historical experience can promote system convergence to an equilibrium state, but excessive reliance on past experiences ($k\ >\ 0.6$ or $\lambda\ <\ 0.5$) hinders convergence. The system will converge when $0 < \sum_{i=1}^{t-1} \omega_i < 1$.

4.2 Dynamic Analysis of Mode Choice Corresponding to VOT in different MaaS scenarios

We expanded the range of VOT variations to observe the mode choice evolution of users with different VOT values. The VOT functions are defined as:

$$
\begin{cases} \alpha_{n^1} = 60 - 50 * \frac{n^1}{N^1}, users\ without\ cars\ n^1 \in N^1 \\ \alpha_{n^2} = 100 - 80 * \frac{n^2}{N^2}, users\ with\ cars\ n^2 \in N^2 \end{cases} \tag{19}
$$

We analyzed two types of transfer travel scenarios:

- **Scenario 1**: ($t_{transfer}^{pt} = 2t_{transfer}^{rpt}$, where the transfer time for public transportcombinations is twice that of public transport + ride-hailing);
- **Scenario 2**: ($t_{transfer}^{pt} = t_{transfer}^{rpt}$, where the transfer time for public transport combinations equals that of public transport + ride-hailing).

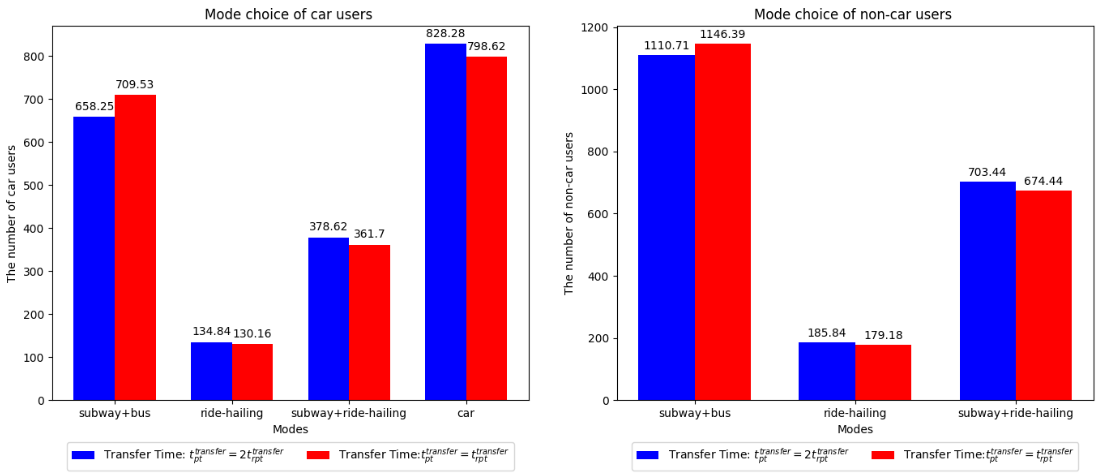
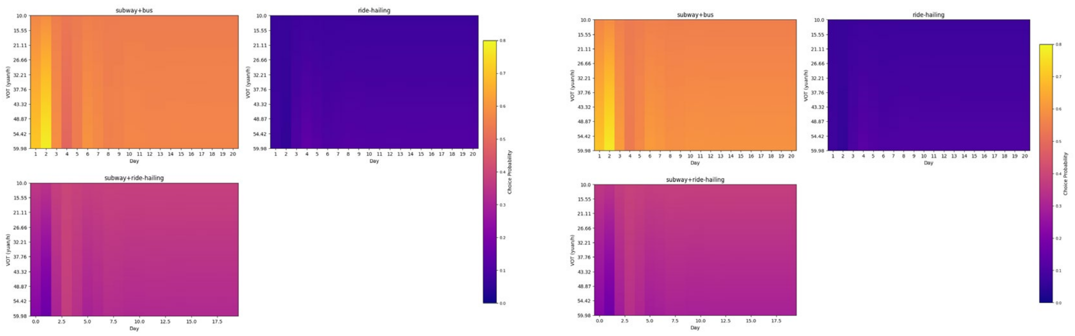


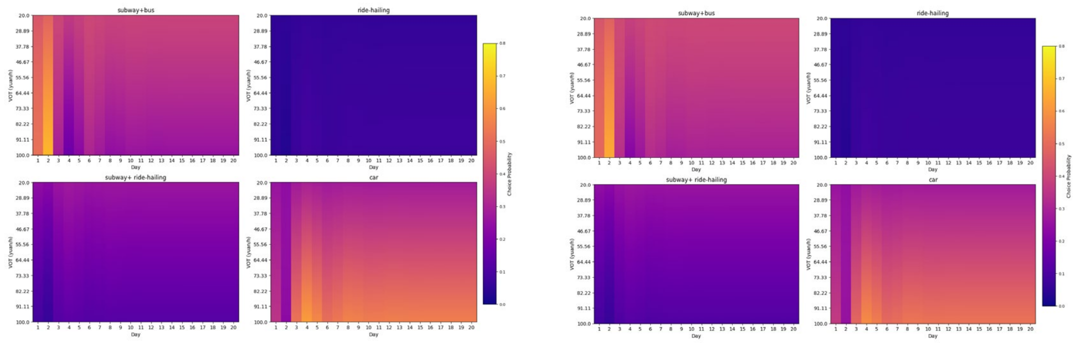
Figure 9: Mode choice of two kind users in different scenarios

The results in figure 9 show that in Scenario 1, the number of users choosing public transport + ride-hailing is higher than in Scenario 2. Additionally, the number of car-owning users choosing private cars is also greater in Scenario 1 than in Scenario 2. The number of ride-hailing users shows minimal change between the two scenarios. Therefore, changes in transfer times for combined travel modes not only affect the number of users choosing these two modes but also influence the number of car-owning users opting for private car travel.



(a) Non-car user mode choice in Scenario 1 (b) Non-car user mode choice in Scenario 2

Figure 10: Evolution of mode choice for non-car users with different VOT in different scenarios.



(a) Car user mode choice in Scenario 1 (b) Car user mode choice in Scenario 2
Figure 11: Evolution of mode choice for car users with different VOT in different scenarios.

We further analyzed the impact of transfer time on the mode choices of users with different VOT in the two scenarios. For non-car owners, the impact of VOT on mode choice is relatively small, and the heterogeneity in mode selection is not very pronounced.

For non-car owners (see figure 10), users with higher VOT have a slightly higher probability of choosing the subway + ride-hailing combined mode in Scenario 2 (where the transfer time for public transport is greater than that for public transport + ride-hailing) compared to Scenario 1. In contrast, the probability of choosing subway + bus is slightly lower in Scenario 2 than in Scenario 1. Low VOT users are less affected.

For car owners (see figure 11), VOT has a much larger effect on mode choice, and the heterogeneity in mode selection is very pronounced. As VOT increases, car owners are more likely to choose private cars, and the attractiveness of combined modes such as subway + bus or subway + ride-hailing decreases. Unlike non-car owners, car owners exhibit significant heterogeneity in their mode choice behavior, suggesting the need for differentiated policy interventions based on VOT characteristics.

5. CONCLUSIONS

Considering users' long-term learning behaviors, this paper proposes a dynamic mode choice evolution model for heterogeneous users. The model approaches users' long-term learning process through a learning rate decay function and simulates the evolution of mode choice for heterogeneous users based on actual MaaS travel scenarios.

The study shows that, regardless of the learning rate parameters, as long as the sum of the decay factors equals 1, the long-term learning model for heterogeneous users will converge to the same equilibrium state. Proper historical experience learning (with learning decay within a reasonable range) can accelerate the convergence of the system. We further studied the impact of transfer times for different travel modes on the choices of non-car and car owners. The results show that reducing the transfer time for public transport combinations promotes users' choice of public transportation. Non-car owners exhibit low sensitivity to VOT, while car owners display significant heterogeneity in their choices. Therefore, differentiated policies are needed, such as providing financial incentives to non-car owners and charging high VOT car owners, in order to encourage multi-modal travel and reduce private car usage.

According to the proposed research framework, future studies could explore differentiated incentive measures tailored to the travel preferences and behaviors of different user groups, fostering a more balanced and sustainable mode choice in urban transportation.

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