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a user-centric shared mobility service design

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From ride-hailing to high-capacity ride-sharing: a user-centric shared mobility service design

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ABSTRACT

Ride-sharing services operated by transportation network companies (TNCs) have the potential to expand capacity and accommodate increasing urban mobility demands, presenting an alternative to traditional ride-hailing services. This study introduces a high-capacity ride-sharing (HCRS) system that leverages user-specific travel choices and incentive-based pricing schemes. This innovative system enhances the dynamic matching problem of HCRS by incorporating a nested choice model and dynamic fare adjustment strategies to boost profitability while encouraging shared travel behaviours. Additionally, a rolling horizon solution approach is employed, including a shared choice set generation algorithm for creating shared alternatives and an Adaptive Large Neighborhood Search (ALNS)-based method for optimal matching. By leveraging a real dataset from Beijing's ride-hailing services, this research underscores that the HCRS service can significantly improve system efficiency and service quality, achieving more than 10.44% reduction in operating costs, and reducing average fares (¥3.31) and emissions (3.49 kg) across various users, compared to traditional ride-hailing services. The findings also demonstrate that users' decision-making is profoundly affected by changes in incentives, highlighting the importance of incentive settings in enhancing user engagement and system performance.

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High-capacity ride-sharing; user choice model; incentive-based pricing schemes

1. Introduction

Ride-hailing services operated by Transportation Network Companies (TNCs) such as Uber, Lyft, DiDi, and Olacabs provide users with efficient and convenient on-demand transportation, facilitated by professional drivers (Meshkani and Farooq 2022; Zhan, Szeto, and Chen 2022). Alongside these services, ride-sharing emerges as an alternative for further reducing congestion (Mitropoulos, Kortsari, and Ayfantopoulou 2021; Tirachini 2020). By enabling multiple passengers to share a ride, particularly during peak hours, ride-sharing

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enhances vehicle occupancy rates and optimises the use of transportation resources (Özkan 2020; Qi et al. 2018; Zalesak and Samaranayake 2021).

However, the potential of shared services to expand capacity and accommodate increasing demand has not yet been fully realised (Kucharski and Cats 2022). Many TNCs have attempted to expand traditional ride-sharing services, such as DiDiBus and RideCo, but these initiatives face challenges in market penetration and limited service coverage. This is due to a compromise in service quality as they try to accommodate more passengers without fully addressing user mobility preferences. Additionally, the lack of effective financial incentives, which are controlled by TNCs, impedes the transition from solo to shared rides. These limitations prevent services like DiDibus from achieving efficiency goals, thereby impacting public trust and perception.

To provide user-friendly shared services, some studies have incorporated user choice decision-making into dynamic matching mechanisms to recognise users' willingness to opt for shared rides (Azadeh et al. 2022; Bian, Liu, and Bai 2020; Dong and Leng 2021). Additionally, pricing schemes have been widely utilised in dynamic ride-sharing to maintain fair-pricing principles and incentivize users to shift from other travel modes to shared rides (Zhang et al. 2020; Zhou, Roncoli, and Sipetas 2023). This integration ensures that the provided service fully accommodates user travel requests and mobility preferences. However, these studies often generalise user behaviours by employing the multimodal logit model to simplify shared alternatives and assuming a uniform response to changes in fare and service quality. Furthermore, incentives that reward significant contributions to sustainability have not been extensively studied, which is crucial for ensuring the long-term viability of ride-sharing systems.

This work aims to tackle these challenges by developing a high-capacity ride-sharing (HCRS) system designed to optimise on-demand shared solutions for heterogeneous travel preferences. It focuses on integrating a user-centric choice mechanism and a dynamic pricing scheme into the optimal matching problem of HCRS services. This integration ensures that the system not only maximises profitability but also provides users with tailored alternatives that cater to their requests and preferences. The proposed system is assessed across various time-frame scenarios using a comprehensive real-world dataset from Beijing's ride-hailing services. We summarise the contribution of the paper as follows:

- We formulate the dynamic HCRS matching problem by incorporating a nested choice model and dynamic fare adjustment strategies. Specifically, user travel choices are influenced by their class-based sensitivities to key factors affecting perceived utilities, while pricing schemes incentivize users to choose shared trips by compensating them for detours and rewarding them for emission savings in shared rides.
- We introduce a tailored rolling horizon approach (RHA) to periodically manage the introduced HCRS operation, where a shared choice set generation process is applied to create shared alternatives, and an ALNS-based approach is proposed for the optimal matching problem in each optimisation cycle.
- We conducted an experiment using a real-world dataset to validate the efficiency of the HCRS system. The HCRS demonstrated significant improvements: (i) A reduction of over 10.44% in operating costs compared to ride-hailing, and an average reduction of 8.32% in emissions compared to ride-splitting. (ii) Average fare reductions of ￥3.31 and

￥1.69, and emission reductions of 3.49 kg and 1.49 kg across all users compared to both services.

The remainder of the paper is structured as follows. Relevant literature is discussed in Section 2. In Section 3, we illustrate the HCRS service. Section 4 presents the problem formulation. Section 5 introduces the solution algorithm. In Section 6, we present the numerical results, and our findings are summarised in Section 7.

2. Related work

Our paper contributes to the research focussed on dynamic ride-sharing, specifically considering user choices and pricing schemes. We begin by defining the concept of HCRS, followed by a literature review exploring dynamic ride-sharing with user choices and pricing.

2.1. High-capacity ride-sharing service modes

Thanks to advanced information technology, TNCs offer diversified app-based ride-sharing services, including car-based and high-capacity ride-sharing. These services meet the needs of both individual travellers and large groups.

Car-based ride-sharing (CRS), including private-car-based carpooling and car-hailing-based ride-splitting, offers a sustainable travel option (Tu et al. 2021). Private-car-based carpooling involves a car owner who shares trips with others to cut costs (Chen et al. 2019; Schreieck et al. 2016), while ride-splitting involves professional drivers transporting strangers to their destinations (Chang et al. 2025; Lokhandwala and Cai 2018; Yan, Levine, and Zhao 2019).

High-capacity ride-sharing (HCRS), exemplified by buspooling and customised bus (CB) services, refers to ride-sharing options that can accommodate more passengers than CRS operated by TNCs (Huang et al. 2020; Liu and Liu 2020). Buspooling typically has limited stops along the route, allowing users to experience express-like services. Additionally, it establishes schedules and routes solely based on passenger demands, ensuring a highly responsive travel experience. In contrast, CB services may experience delays in updates and have limited responsiveness (Liu and Ceder 2015; Wang, Ma, and Daniel Xu 2020). The specific differences in service features are summarised in Table 1. The HCRS discussed in this document primarily relates to buspooling operated by TNCs.

Table 1. Comparison of service features between HCRS and CRS.

	HCRS		CRS	
Service feature	CB	Buspooling	Ride-splitting	Carpooling
Route	Periodic update	On-demand	On-demand	On-demand
Intermediate stops	Some, bus-stop	Few, ad hoc	One or two, ad hoc	One or two, ad hoc
Fare level	Low	Mid-low	High	Mid-high
Vehicle type	Medium/large	Medium	Small	Small
Usage mode	Online	App of TNCs	App of TNCs	App of TNCs
Driver	Professional	Professional	Professional	Users

2.2. Dynamic ride-sharing with user choices and pricing

Recent studies have incorporated user choice behaviours into the joint pricing and matching of shared services, as understanding user travel behaviours and applying fair-cost sharing mechanisms are both crucial for optimising dynamic ride-sharing and promoting the adoption of shared rides (Xiong et al. 2020; Zhan, Szeto, and Chen 2022).

User choice decision-making is significantly influenced by key factors such as in-vehicle travel time, fare, comfort, safety, and other service attributes (Arora, Zheng, and Girotra 2024; Peng, Teng, and Wang 2024). Discrete choice models have been widely used to estimate user choices in shared services by quantifying user-perceived utilities when they join services (Lyu et al. 2019). For instance, Dong et al. (2022) applied a binary logit (BL) model within the chance constraints of the dial-a-ride problem (DARP) to capture users' preferences between DARP services and private travel options, a similar approach to that seen in Dong and Leng (2021). When the options become more complex and diverse, Azadeh et al. (2022) and Azadeh, van der Zee, and Wagenvoort (2022) explored the multinomial logit (MNL) model in on-demand DARP and demand-responsive transit systems, estimating the willingness of users with considerations such as price, ride time, and delayed pickup time. MNL has also been applied to other mobility services (Ren, Chow, and Guan 2024; Zhou, Roncoli, and Sipetas 2023) to estimate user choices between solo, shared, and other options. When choice alternatives can be logically grouped into subsets based on similar characteristics, the nested logit (NL) model is essential for considering potential correlations in unobserved factors within these groups (Spurlock et al. 2019; Yoon, Cherry, and Jones 2017). For example, Winter et al. (2020) explored the integration of NL and latent class choice models to capture the heterogeneity (e.g. vehicle ownership, education, income) in user preferences.

Dynamic ride-sharing benefits from joint pricing and matching strategies that improve market segmentation and profitability, influencing users' acceptance of shared rides (Wang and Yang 2019; Xu, Saberi, and Liu 2022). Existing pricing schemes include optimisation-based and rule-based approaches (Ding et al. 2023; Yan et al. 2021). Optimization-based methods are characterised by a formal objective metric, such as maximising profit or revenue, or minimising cost or dissatisfaction. Examples can be seen in Kanoria and Qian (2023) and Özkan (2020). These studies demonstrated that this joint optimisation can lead to lower fares, improved vehicle utilisation, and increased welfare. On the other hand, rule-based approaches apply predetermined rules to set prices, which are commonly used to maintain demand-supply equilibrium in the market (Banerjee, Riquelme, and Johari 2015). Surge pricing, a common rule-based method, has been extensively studied and is designed for a two-sided market, aiming to balance supply and demand in matching, as seen in Miao et al. (2023). Additionally, various incentive mechanisms have been investigated to enhance user acceptance of shared rides. Yang et al. (2020) integrated a reward scheme into surge pricing to address peak and off-peak hour users, finding that the generated rewarding strategies were beneficial for all three stakeholders, i.e. passengers, drivers, and the platform. Bian et al. (2022) proposed an intermediate pricing layer that differentiated between scheduled and on-demand passengers to promote early scheduling and ensure financial sustainability by incentivizing regular commuters. Zhou, Roncoli, and Sipetas (2023) introduced a multiplicative discount function in the choice-based Mobility-on-Demand (MoD) framework that accounted for the detour and sharing index, compensating users accordingly.

Table 2. Review summary.

Author	Research object	User class	Choice model	Pricing
Huang et al. (2020)	HCRS	×	MNL	×
Yang et al. (2020)	CRS	×	×	Dynamic
Azadeh, van der Zee, and Wagenvoort (2022)	HCRS	×	MNL	Static
Dong et al. (2022)	CRS(DARP)	✓	BL	Static
Bian et al. (2022)	CRS	✓	×	Dynamic
Azadeh et al. (2022)	CRS(DARP)	×	MNL	Dynamic
Zhou, Roncoli, and Sipetas (2023)	CRS	×	MNL	Dynamic
Ren, Chow, and Guan (2024)	CRS,HCRS	×	MNL	×
This work	HCRS	✓	NL	Dynamic

Table 2 presents a summary of the studies reviewed in this section and compares them to the study we propose. Despite significant advancements in the study of car-based shared mobility, the dynamics of high-capacity ride-sharing services have received limited attention. Furthermore, the complexities of shared travel alternatives, distinct user classes, and their sensitivities to service attributes have not been fully considered in HCRS. Additionally, the incentive-based pricing scheme that considers emission reductions from shared rides has yet to be thoroughly investigated. Thus, this work introduces a HCRS system that integrates class-based user choices and dynamic pricing schemes, aiming to facilitate a transition from ride-hailing to HCRS.

3. High-capacity ride-sharing service

The proposed HCRS service is designed to offer an on-demand shared mobility solution catering to heterogeneous travel preferences, aiming to maximise the marginal operational profit of TNCs. This framework enables HCRS dynamically adapt to demand fluctuations, providing a responsive and efficient service.

In HCRS, users, denoted by $p \in P_N(t)$, submit their travel requests in real time, detailing their origin, destination, preferred departure and arrival time, represented as $TR_p = \langle o_p, d_p, dep_p, arr_p \rangle$. Additionally, the mobility preference of each user is reported, specifying the tolerable waiting time, detour, and the number of tolerable shared users $MP_p = \langle w_p, dt_p, s_p \rangle$. It is assumed that each user submits their travel request independently. Thus, users select their preferred travel alternative, either ride-hailing or HCRS, or opt-out for other modes (such as taxi), based on individual preferences and sensitivities regarding preliminary fares, travel time, and comfort levels. To enhance the HCRS's ability to offer personalised service options, HCRS incorporates a nested choice model to estimate the user travel choices, where users are allowed to choose ride-hailing or opt-out options instead of HCRS. However, once a user opts into HCRS, the current framework does not allow any subsequent cancellation (i.e. after the vehicle is assigned).

The planning process of HCRS is depicted in Figure 1, showcasing its dynamic and responsive nature. The system employs a Rolling Horizon Planning (RHP) strategy. To simplify the planning and execution of the system. The planning horizon, T is divided into discrete intervals, denoted as micro period $t \in \{0, \ldots, T\} = \mathcal{T}$. Within each interval, t (e.g. 1 min), user travel requests are collected into batches. At the end of each interval, vehicles characterised by specific states are deployed to identify shared trip options to satisfy the travel requests and mobility preferences of each new/on-board user. An optimisation

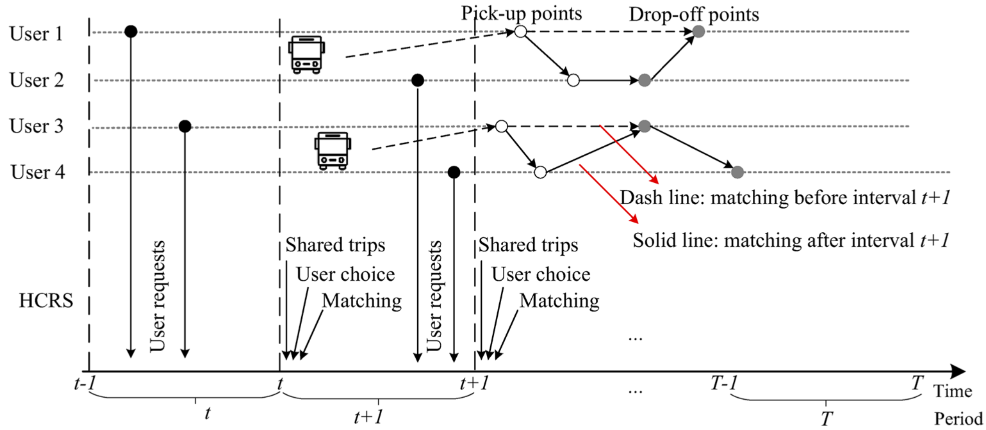

Figure 1. The planning process of HCRS.

process follows, determining the optimal matching plan to maximise expected marginal profit based on current collected demand data. This periodic optimisation allows HCRS to continuously adapt to demand changes, incrementally improving profitability with each cycle. Importantly, the HCRS operates on a first-come, first-served (FCFS) basis throughout the entire planning period, giving priority to users in earlier batches over those in later ones. In each individual cycle, the system employs a one-to-one assignment strategy, which permits assigning multiple users to a single vehicle across different optimisation cycles. A key feature of HCRS is its incentive strategies, which dynamically adjust fares to compensate users for increased detours and emission savings on shared trips. Specifically, preliminary fares are presented to new users based on shared trips, and fares for on-board users are adjusted in response to new requests to maintain fairness and profitability.

3.1. Event sequences

The event sequence is as follows (see Figure 2): (1) users arrive and submit travel requests and mobility preferences; (2) given the requests and the current vehicle states, the HCRS generates a set of feasible shared alternatives that match the preferences; (3) users are presented with these alternatives, and a choice model estimates the probability that the user selects each option; (4) after the user choice is simulated, HCRS determines the optimal match, and updates the vehicle states accordingly; (5) users are informed of the final assignment configuration as soon as the vehicle is en-route for picking up.

3.2. Vehicle states

During each interval t, a fleet of homogeneous vehicles ($k \in K(t)$) is categorised into one of three statues: idle ($k \in K_I(t)$), en-route for pickup ($k \in K_{EP}(t)$) and en-route for delivery ($k \in K_{ED}(t)$). The vehicle state is defined by its location, route, corresponding visiting time, and remaining capacity, denoted as $s_k(t) = \langle l_k(t), r_k(t), t_k(t), cap_k(t) \rangle$, and is updated at each t with the arrival of new users.

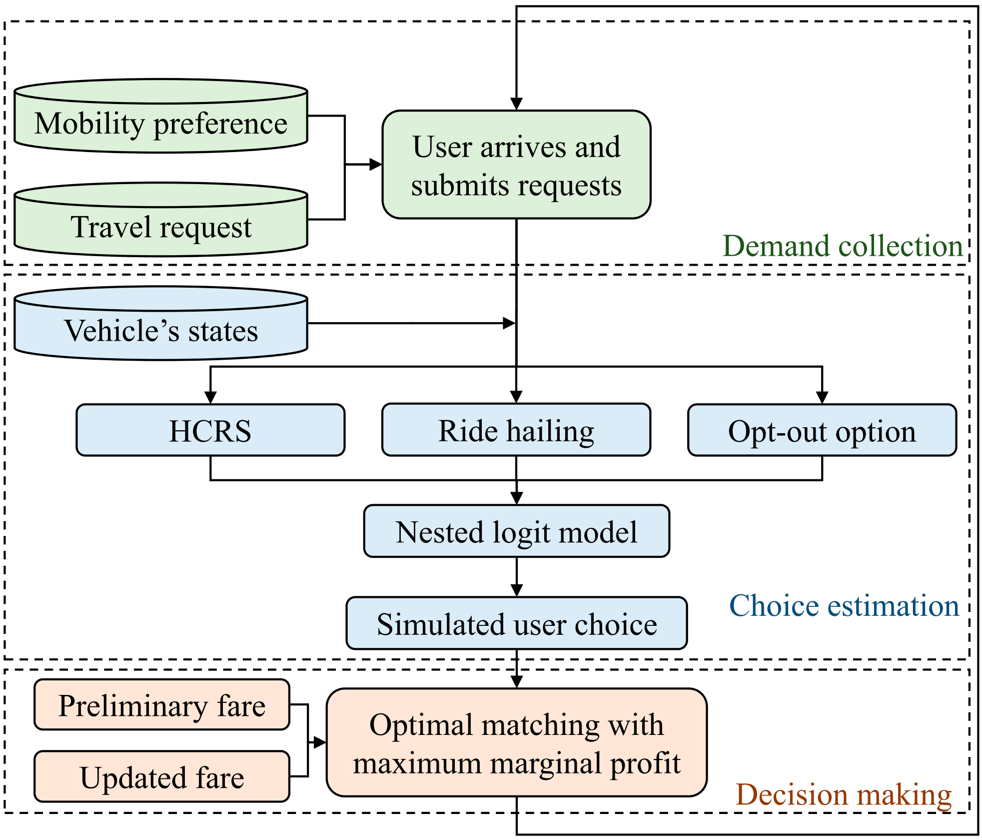

Figure 2. Event sequence of the HCRS.

4. User choice model

This work studies the choice scenario where users select among three travel modes: ride-hailing, HCRS, and an opt-out category representing other available alternatives. Given the assumption that each user selects the trip with their maximum utility, this section aims to develop a decision-support tool to capture user choice preferences based on these modes. The model treats the choice probabilities as input parameters for each new user when they appear. Table 3 outlines the parameters utilised in the user choice model. To account for the complexity of travel choices, particularly within the HCRS category, the model employs a nested structure. In this structure, each nest ($n \in N$) contains multiple alternatives, i.e. choices that share common characteristics within each mode:

- ride-hailing nest (n^R): this nest refers to solo travel alternatives and typically includes one alternative provided by a private ride-hailing service, as the solo trip is considered as the most direct option, with no variability in route or schedule.
- HCRS nest (n^H): this nest includes a variety of shared travel alternatives, with multiple vehicles offering different routes and schedules, all facilitated by en-route and idle vehicles within the HCRS.

Table 3. Parameters in choice model.

Notation	Description
Set	
$\mathcal{T}$	Set of time intervals
$P_N(t), P_I(t), P_U(t)$	Sets of new, in-vehicle and assigned yet visited demands at t
$K_I(t), K_{EP}(t)$	Set of idle, en-route for pickup vehicles at t
C	Set of user classes
N	Set of nests, $N = \{n^R, n^H, n^O\}$
C_p^H	Shared choice set of user p, $C_p^H = \{a, attr_p^a \mid a \in n_p^H\}$
Parameter	
TP_p	Travel request of user p, including origin o_p, destination d_p, preferred departure and arrival time dep_p, arr_p
MP_p	Mobility preference of user p with tolerable waiting time w_p, detour dt_p and the number of tolerable shared users s_p
$s_k(t)$	State of vehicle k at t, with location $l_k(t)$, route $r_k(t)$,visiting time $t_k(t)$, remaining capacity $cap_k(t)$
$Prob_p(a)$	Probability for user p choose alternative a
$Prob_p(n), Prob_p(a\|n)$	Probability of choosing a nest and an alternative a within n
$\Gamma_{p,n}$	Logsum variable of nest n
λ_n	Dissimilarity parameter for nest n
U_p^H, U_p^R, U_p^O	Utility of HCRS, ride-hailing, and opt-out mode of user p
ASC^H, ASC^R, ASC^O	Parameters of inherent trip qualities with different modes
f_p^H, f_p^R	User fares of HCRS and ride-hailing for user p
f_0, f_d, f_t	Fixed fare, distance and time fare rates
$dist_p, tt_p$	Distance and travel time of user p with ride-hailing
tt_p^H	Travel time with HCRS
cl_p^H	Comfort reduction of user p, related to shared in-vehicle time st_p^H
$\beta_f^c, \beta_t^c, \beta_o^c$	Class-based coefficients of fare, travel time, and comfort reduction
c_f, c_d	Fixed vehicle departure cost and running cost per distance
γ_e	Emission (CO2) generated per distance
$attr_p^a$	Attributes of alternative a: preliminary fare $\hat{f}_p^a$, travel time tt_p^a, shared in-vehicle time st_p^a, shared users s_p^a, detour dt_p^a, emission reduction e_p^a and operating cost oc_p^a
$oc_p^k(t)$	Operating cost of serving user p with k at time t
$\Delta dt_p^k(t), \Delta e_p^k(t)$	Additional detours and emission reduction for on-board user p with vehicle k at time t
$dist(r_p^a)$	Route distance for serving new user p with alternative a
$dist(r_p^k(t))$	Route distance for serving on-board user p with vehicle k at t
$dist_{i,j}$	Distance of arc (i,j)
$s_{i,j}^a$	Number of shared users on arc (i,j) of alternative a
$s_{i,j}^k(t)$	Number of shared users on arc (i,j) of vehicle k at t

- Opt-out nest (n^O): this category involves external alternatives not under the ride-hailing or HCRS categories. Here, we only consider one option, representing the best alternative, such as taxi.

Thus, the choice probability for user p choose alternative a can be formulated into a nested logit (NL) model (Koppelman and Wen 1998):

$$Prob_p(a) = \sum_n Prob_p(a \mid n) \cdot Prob_p(n) \tag{1}$$

$$Prob_p(a|n) = \frac{\exp(U_p^a(n)/\lambda_n)}{\sum_{a'} \exp(U_p^{a'}(n)/\lambda_n)} \tag{2}$$

$$Prob_p(n) = \frac{\exp(\lambda_n \Gamma_{p,n})}{\sum_{n'} \exp(\lambda_{n'} \Gamma_{p,n'})} \tag{3}$$

$$\Gamma_{p,n} = \ln\left(\sum_{a' \in N_n} \exp\left(\frac{U_p^{a'}(n)}{\lambda_n}\right)\right) \tag{4}$$

where $U_p^a(n)$ represents the utility function of alternative a within nest n, and $\lambda_n \in (0, 1]$ is the dissimilarity parameter for nest n. Given that the ride-hailing options and opt-out options have no correlations within the corresponding nests, the values of λ_n^R and λ_n^O are set as 1 to illustrate there is no similarity of options (Wen and Koppelman 2001). The detailed parameter setting is given in Section 7.1.4.

4.1. Utility function

The user utilities associated with the available travel alternatives, including both ride-hailing and shared (HCRS) options, are influenced by factors:

- For ride-hailing mode, i.e. solo trips, the user utility U_p^R is associated with the fare f_p^R and travel time tt_p, since it offers a direct, non-shared trip.
- For HCRS mode, the utility U_p^H is influenced by the fare f_p^H, travel time tt_p^H, and comfort reduction cl_p^H, which accounts for the shared nature of the trip.

Given the diversity of user preferences in the shared and ride-hailing market, where some users prioritise fares while others are more sensitive to service quality (Zhan, Szeto, and Chen 2022), we categorise users into distinct classes based on their travel patterns. Let $C = \{1, 2, \ldots |C|\}$ be the set of classes. Each user p can be categorised into one of these classes. The utility functions for the HCRS, ride-hailing, and opt-out travel alternatives within the corresponding nests are as follows.

$$U_p^H(c) = ASC^H - \beta_f^c f_p^H - \beta_t^c ttp^H - \beta_o^c cl_p^H \tag{5}$$

$$U_p^R(c) = ASC^R - \beta_f^c f_p^R - \beta_t^c tt_p \tag{6}$$

$$U_p^O = ASC^O \tag{7}$$

where ASC^H, ASC^R and ASC^O represent alternative-specific constants that capture differences across the HCRS, ride-hailing, and opt-out options, such as perceived safety, reliability, etc., β_f^c, β_t^c, and β_o^c are the class-based utility coefficients to convert fare, trip time and comfort reduction into the users' perceived utility, tt_p is the travel time of user p with ride-hailing, which is the direct trip. Here, the comfort reduction cl_p^H is related to the shared in-vehicle time (S-IVT) st_p^H, especially for the high-capacity shared services (Barone et al. 2018; Liu et al. 2020; Shen et al. 2016).

For the utility function of ride-hailing, we use the standard fare structure commonly employed by DiDi (Zhou, Roncoli, and Sipetas 2023). The fare details for HCRS are outlined in Section 5.1.

$$f_p^R = f_0 + f_d dist_p + f_t tt_p \tag{8}$$

where f_0 is the fixed base fee, f_d and f_t are fare rates of distance and time, respectively, $dist_p$ and tt_p are the travel distance and time of user p with ride-hailing.

4.2. Choice set generation

In the NL model framework, each user p's choice set (C_p) is organised into three distinct nests. Within the HCRS nest, the choice set (C_p^H) is notably complex, consisting of various alternatives characterised by different trip configurations (such as routes, schedules, detours, number of on-board users). The attributes for each alternative are derived from these trip configurations, as outlined in Section 4.3. This complexity arises from the integration of user-specific requests and preferences with the dynamics of vehicles that are either en-route for pickup or idle ($k \in K_{EP}(t) \cup K_I(t)$), along with their on-board users.

The generation process for C_p^H in nest n_p^H extends the standard demand insertion techniques used in demand-responsive transit services (Huang et al. 2020) by integrating the mobility preferences of both new user $p (p \in P_N(t))$ and those already on board ($P_U(t) \cup P_I(t)$) at t, where $P_U(t)$ and $P_I(t)$ are the sets of assigned yet unvisited and currently in-vehicle users, respectively. The process constructs each shared alternative a, which includes detailed specifications of routes, schedules, and the current status of all users on-board the respective vehicle. Specifically, given a set of vehicle state $s_k(t-1) (k \in K_{EP}(t-1) \cup K_I(t-1))$, which captures the vehicles' last known locations, routes, schedules, and capacities, a greedy algorithm–referred to as the shared choice set generation algorithm (detailed in Section 6.2)–is employed to derive a set of alternatives a. Each alternative a is linked to a specific vehicle k, proposing feasible routes and schedules that could potentially accommodate user p. Each directed link (i, j) is associated with a travel time $tt_{i,j}(t)$ from vertex i to j departing from time t.

Importantly, this algorithm generates hypothetical scenarios for routes and schedules that optimise the integration of new and existing passengers without disrupting the ongoing operations of vehicle k. The state $s_k(t)$ will not change until user p has been matched with alternative a (that corresponds to vehicle k):

$$s_k(t) = s_k(s_k(t-1), x_p^a(t)). \tag{9}$$

where $x_p^a(t)$ is the matching decision, $= 1$, indicates user p is matched with alternative a; $= 0$, otherwise.

4.3. Alternative attributes

Given the choice set $C_p^H = \{a, attr_p^a | a \in n_p^H\}$ for serving new user p, each alternative a within the HCRS framework is defined based on the trip configuration. These configurations serve as the foundation for the attributes that influence user choices. The attributes associated with each alternative a are defined as follows, with differences made between new users and on-board users.

Attributes for new users. The shared option a of new user $p (p \in P_N(t))$ is associated with a tuple of attributes. These attributes $attr_p^a$ are used to determine the probability of user p choosing each option a ($Prob_p^a$):

- Preliminary fare $\hat{f}_p^a$, initially estimated fare for using alternative a, as detailed in Section 5.1.
- Actual travel time tt_p^a: $tt_p^a = t_{d_p}^a - t_{o_p}^a$, where $t_{o_p}^a$ and $t_{d_p}^a$ are the visiting times at origin o_p and destination d_p with alternative a.
- Shared in-vehicle time st_p^a and the number of shared users s_p^a.
- Detour dt_p^a and emission reduction e_p^a if user p travels with alternative a compared to ride-hailing service.

$$dt_p^a = dist(r_p^a) - dist_p; \quad e_p^a = \gamma_e \sum_{(i,j)\in r_p^a} (dist_{i,j} - dist_{i,j}/s_{i,j}^a) \tag{10}$$

  where $dist(r_p^a)$ is the distance of designed route for serving p with alternative a, $s_{i,j}^a$ is the number of shared users on arc (i,j) with alternative a, γ_e signifies the emission per distance.
- Operating cost oc_p^a of serving p, c_f and c_d are the fixed vehicle departure and running cost per additional travel distance.

$$oc_p^a = c_f/s_p^a + c_d \cdot (dist(r^{k,a}) - dist(r^k)) \tag{11}$$

  where $dist(r^{k,a})$ is the distance of vehicle k when it is used as alternative a for serving p, $dist(r^k)$ is the distance of the vehicle k before user p is assigned to vehicle k.

Attributes for on-board users. For on-board users ($p' \in P_I(t) \cup P_U(t)$) who are already matched with vehicle k during the previous time step, the integration of new user p necessitates updating certain attributes at time t. These updates reflect changes in the travel environment to the existing route of vehicle k:

- Additional detour $\Delta dt_{p'}^k(t)$, the extra distance of on-board user p' travels with vehicle k to accommodate p without disrupting the journey of p'.

$$\Delta dt_{p'}^k(t) = dist(r_{p'}^k(t)) - dist(r_{p'}^k(t-1)) \tag{12}$$

  where $r_{p'}^k(t)$ and $r_{p'}^k(t-1)$ represent the routes for user p' after and before the insertion of p. Initially, $r_{p'}^k(t-1)$ is set to $r_{p'}^a$.
- Additional emission reduction $\Delta e_{p'}^k(t)$, resulting from an increase in the number of shared users on each route segment due to new user p joining. The calculation is based on the change in the number of shared users on each arc (i,j) along user p''s route before $s_{i,j}^k(t-1)$ and after $s_{i,j}^k(t)$ the new user insertion.

$$\Delta e_{p'}^k(t) = \gamma_e \sum_{(i,j)\in r_{p'}^k(t)} dist_{i,j}(s_{i,j}^k(t) - s_{i,j}^k(t-1)) \tag{13}$$

  where $s_{i,j}^k(t-1)$ is initially set to $s_{i,j}^a$.
- Operating cost $oc_{p'}^k(t)$, resulting from the increase of the new shared user p, is calculated with $oc_{p'}^k(t-1)$ and the number of shared users serving by vehicle k at t, i.e. $s^k(t)$. $oc_{p'}^k(t-1)$ is initially set as $oc_{p'}^a$.

$$oc_{p'}^k(t) = oc_{p'}^k(t-1) - c_f/s^k(t) \tag{14}$$

5. Mathematical model

5.1. Dynamic fare adjustment strategies

This section outlines the fare adjustment strategies implemented in HCRS. For each new user p, a preliminary fare $\hat{f}_p^a$ for an alternative a is initially determined. It is important to note that $\hat{f}_p^a$ is not the final charge; rather, it serves as a baseline from which fare adjustments are made. Once user p is on board, the fare undergoes recalculation. This adjustment accounts for new users joining the ride and incorporates incentives for sharing, and any necessary detours required. The fare adjustment process is iterative, and the final fare f_p^* is determined once no further users are added to the trip. The related parameters please see Table 4.

To ensure fairness for both new and on-board users and the financial profitability of TNCs, we suggest the following guidelines:

- Fares for shared trips should be lower than those for solo trips.
- The fare structure must at least cover the operating costs of serving a new passenger to ensure the service's economic viability.
- Incentives for users should increase as detour length increases, provided that these detours remain within the tolerable detour distance.
- Users who contribute to significant emission reductions by sharing rides should receive greater incentives.
- The final fare charged should not exceed the preliminary fare.

Preliminary fare of new users. For each new user $p(p \in P_N(t))$ at time step t, the preliminary fare $\hat{f}_p^a$ for alternative a is derived from the solo travel fare (f_p^R) to reflect cost savings from detours dt_p^a and shared emission reductions e_p^a, which are the given attributes of alternative a. The preliminary fare is calculated as follows:

$$\hat{f}_p^a = f_p^R - \epsilon_d dt_p^a - \epsilon_e e_p^a, \quad \forall p \in P_N(t) \tag{15}$$

$$\hat{f}_p^a \geq oc_p^a, \quad \forall p \in P_N(t) \tag{16}$$

where ϵ_d and ϵ_e stand for the incentives offered for each unit of distance and emission reduction, respectively, oc_p^a is the operating cost of serving user p, as detailed in Section 4.3.

Updated fare of on-board users. The fare of on-board user $p(p \in P_I(t) \cup P_U(t))$ who have already assigned to vehicle k, is updated iteratively every time step t upon the arrival of a

Table 4. Parameters in model.

Notation	Description
Parameters	
$\mathcal{P}_p^k(t)$	Profits of vehicle k at time t
$\hat{f}_p^k$	Preliminary fares of user p with vehicle k, related to alternative a
$f_p^k(t)$	Updated fare of on-board user p served by vehicle k at t
f_p^*	Final fare of user p
$Prob_p^k$	Probability of new user p choosing vehicle k, related to alternative a
$\Delta dt_p^k(t), \Delta e_p^k(t)$	Additional detours and emission reduction for on-board user p with vehicle k at time t
ϵ_d, ϵ_e	Incentives per unit of distance and emission saving
Decision variable	
$x_p^k(t)$	Binary variable, $=1$, indicates new user $p(p \in P_N(t))$ is assigned to vehicle k, corresponding to alternative a; $=0$, otherwise

new user into the trip. This addition can lead to modifications in the trip's route and adjustments in user distribution. Such changes may result in additional detours ($\Delta dt_p^k(t)$) and potential emission reductions ($\Delta e_p^k(t)$). The fare is updated repeatedly until no further user insertion occurs:

$$f_p^k(t) = f_p^k(t-1) - \epsilon_d \Delta dt_p^k(t) - \epsilon_e \Delta e_p^k(t), \quad \forall\, p \in P_U(t) \cup P_I(t) \tag{17}$$

$$f_p^k(t) \geq oc_p^k(t), \quad \forall\, p \in P_U(t) \cup P_I(t) \tag{18}$$

where $f_p^k(t-1)$ and $f_p^k(t)$ denote the updated fares for on-board user p before and after the integration of new users, respectively. Initially, when user p joins the service, $f_p^k(t-1)$ is set equal to $\hat{f}_p^a$, and $oc_p^k(t)$ equals to oc_p^a, with the chosen alternative a corresponding to vehicle k. Once no further new user insertion occurs, the final fare is determined as $f_p^* = f_p^k(t)$.

5.2. Optimal matching for HCRS

To address the optimal matching problem in HCRS that incorporates user choices, a set of new users is matched with available vehicles in each optimisation cycle, where the process is structured as an assignment problem to achieve the best matching plan based on current users. Within this framework, we employ a one-to-one assignment strategy, which allows for the possibility of assigning multiple users to a single vehicle across different optimisation cycles (Table 4).

Given the decision variable $x_p^a(t)$, here, we modify this variable to $x_p^k(t) \in \{0,1\}, \forall p \in P_N(t), k \in K_I(t) \cup K_{EP}(t), t \in \mathcal{T}$, as each alternative a is linked to a specific vehicle k. Similar change can be seen in $Prob_p^k$, $\hat{f}_p^k$.

Objective. The objective is to maximise the marginal profit that is the expected value of TNCs at time t, with a focus on immediate benefits in each optimisation cycle, aiming to flexibly respond to demand fluctuations and dynamically optimise resource allocation.

$$\max \sum_{k \in K_I(t) \cup K_{EP}(t)} \left(\mathcal{P}_p^k(t) - \mathcal{P}_p^k(t-1)\right) \tag{19}$$

$$\mathcal{P}_p^k(t) = \sum_{p \in P_N(t)} Prob_p^k(\hat{f}_p^k - oc_p^k) x_p^k(t) + \sum_{p \in P_I(t) \cup P_U(t)} \left(f_p^k(t) - oc_p^k(t)\right) \tag{20}$$

where $\mathcal{P}_p^k(t-1)$ and $\mathcal{P}_p^k(t)$ are the profits of vehicle k before and after batched users ($p \in P_N(t)$) join.

Assignment constraints. Equations (21)–(22) ensure the one-to-one assignment between users and vehicles.

$$\sum_{k \in K_I(t) \cup K_{EP}(t)} x_p^k(t) \leq 1, \quad \forall\, p \in P_N(t) \tag{21}$$

$$\sum_{p \in P_N(t)} x_p^k(t) \leq 1, \quad \forall\, k \in K_I(t) \cup K_{EP}(t) \tag{22}$$

s.t. Equations (1)–(18).

6. Solution approach

6.1. A rolling horizon framework

The proposed HCRS framework utilises a rolling horizon approach to optimally match users and vehicles within the planning horizon, addressing both economic feasibility and environmental sustainability.

The rolling horizon framework is outlined in Algorithm 1. In each period t, users are first batched and grouped into different classes. Given the batched user requests and mobility preferences, available vehicles for these batched users are identified, and the travel choice sets (i.e. potential shared trips) are generated, as detailed in Section 6.2. Subsequently, in Section 6.3, we tackle the large-scale optimal matching problem using the ALNS approach, where three tailored destroy and repair operators are employed. Once the matching is established, the vehicle states are updated, which are then used for the next period's matching. This cycle continues until the conclusion of the planning horizon.

Algorithm 1: Rolling horizon approach

Input: Initial vehicle states $\{s_k(0) \mid k \in K_I(0) \cup K_{EP}(0)\}$, new users $\{p \mid p \in P_N(t)\}$ at $t(t \in \mathcal{T})$, corresponding TR_p and MP_p

Output: best matching solution $\mathbf{x}(\mathbf{t})$ of each period

set $t = 1$;
while $t \leq \mathcal{T}$ **do**
  for $p \in P_N(t)$ **do**
    $C_p^H = GenerateChoiceSet(\{s_k(t) \mid k \in K_I(t) \cup K_{EP}(t)\}, TR_p, MP_p)$ ← Apply Algorithm 2 to generate shared choice sets;
    $\{Prob_p^a \mid \forall a \in n_p^H\} = EstimateChoice(C_p^H, U_p^H, U_p^R, U_p^0)$ ← Estimate the user choice probability with Eqs.(1)-(11);
  $\mathbf{x}(\mathbf{t}) = ALNS(\mathbf{Prob}, \mathbf{C}, K_I(t) \cup K_{EP}(t))$ ← Determine optimal matching;
  for $k \in K_I(t-1) \cup K_{EP}(t-1)$ **do**
    $s_k(t) = s_k(s_k(t-1), \mathbf{x}(\mathbf{t}))$ ← Update vehicle states;
  $t = t + 1$;

6.2. Shared choice set generation process

This section outlines the generation of the shared choice set as described in Section 4.2. A Greedy algorithm, incorporating the introduced dynamic fare adjustment strategies, is presented. A vehicle is considered available to produce a shared alternative if it meets the following criteria: (i) the vehicle is idle or en-route for pickup; (ii) sufficient remaining capacity is available; (iii) the generated shortest trip satisfies the travel requests and mobility preferences of both new and on-board users; and (iv) the fares for on-board users are updated with the insertion of new users.

Algorithm 2 presents the details of the algorithm. For each vehicle, the process begins by identifying its state $s_k(t)$. Next, the feasibility of possible insertion points in the visiting sequence is evaluated to find the shortest sequence. After that, the operating cost and fares are updated. This process is repeated for each vehicle until all have been thoroughly examined.

6.3. Matching optimisation with ALNS approach

In our study, we use the ALNS algorithm to solve the large-scale matching problem between HCRS vehicles and users, as it efficiently navigates complex solution spaces. ALNS

Algorithm 2: Shared choice set generation

Input: Vehicle states $\{s_k(t-1) \mid k \in K_I(t-1) \cup K_{EP}(t-1)\}$, New user $p \in P_N(t)$ and on-board users $\{p' \mid p' \in P_I(t) \cup P_U(t)\}$, with their travel request $TP_p = < o_p, d_p, dep_p, arr_p >$ and mobility preference $MP_p = < w_p, dt_p, s_p >$

Output: Shared choice set $C_p^H = \{(a, attr_p^a) | a \in n_p^H\}$

for $k \in K_I(t-1) \cup K_{EP}(t-1)$ **do**
  if $cap_k(t-1) > 0$ **then**
    $(o^i, n) = FindL(l_k(t-1), r_k(t-1))$ ←Find the first insert point and the number of nodes;
    for $i \leq n-1$ **do**
      $j = 1$;
      for $j \leq n$ **do**
        $r_{i,j}^k = < o^i, o_p, \ldots, d^j, d_p, \ldots, d^n >$ ← Insert o_p and d_p;
        $t_{i,j}^k = < t_{o^i}^k, t_{o_p}^k, \ldots, t_{d^j}^k, t_{d_p}^k, \ldots, t_{d^n}^k >$ ←Visiting time;
        if $CheckPreference(r_{i,j}^k, t_{i,j}^k, TP_p, MP_p)$ *is true* **then**
          save $r_{i,j}^k, t_{i,j}^k$;
        $j = j + 1$;
      $i = i + 1$;
    $r_k = r_{i,j}^k, t_k = t_{i,j}^k, where(i,j) = \arg\min_{i,j} dist_{i,j}^k, 1 \leq i,j \leq n$;
    Calculate $attr_p^a(a \to k)$ with r_k, t_k ;
    $\hat{f}_p^a = PreliminaryFare(dt_p^a, e_p^a)$ ←Create preliminary fare;
    $f_{p'}^k(t) = UpdateFare(f_{p'}^k(t-1), \Delta dt_{p'}^k(t), \Delta e_{p'}^k(t))$ ←Update fare for p';
$C_p^H = \{(a, attr_p^a) | a \in n_p^H\}$;

is particularly well-suited for this role due to its ability to handle the high volume of user requests and adapt quickly at each time step, crucial for managing the extensive time horizon and dynamic user-vehicle allocations (He, Jin, and Schulte 2024; Syed et al. 2019).

The ALNS approach begins by establishing the initial solution through the generation of shared choice sets C_p^H, choice probabilities $\{Prob_p^a\}$ for each new user ($p \in P_N(t)$) and available vehicle ($K_I(t) \cup K_{EP}(t)$). We introduce three tailored destroy-repair operators, designed for the neighbourhood search, which are randomly selected based on their weights. Simulated annealing is integrated to guide the search effectively, dynamically adjusting operator weights based on their solution-generating performances with a roulette wheel selection mechanism, as given in Pisinger and Ropke (2007). This strategy not only refines the search process but also allows the acceptance of new solutions based on calculated probabilities, thereby enhancing the exploration of the solution space and preventing convergence to local optima.

Construction of initial solution. To generate initial solutions for matching users to vehicles in a transportation network, the process involves using a predefined choice set of alternatives C_p^H for each user $p(p \in P_N(t))$, featuring detailed attributes. The steps are: (i) sort each user's alternatives by fares to identify the most cost-effective option; (ii) select the lowest fare alternative for each user to ensure cost-efficiency in initial matches. If a vehicle is already matched with other users, it becomes unavailable for new users. These selected alternatives establish the initial user-vehicle pairings, setting the stage for further optimisation to enhance service quality and user satisfaction.

Destroy and repair operators. We implement three paired destroy-repair operators to improve the matching solution **x**. Each destroy operator is directly followed by a corresponding repair operator, which can be targeted to recover a corresponding disruption.

These pairing operators are designed to efficiently address specific matching challenges. In each cycle, a destroy-repair pair is selected based on dynamically adjusted weights, reflecting recent performance of each pair. This approach prioritises pairs with higher success rates, improving the algorithm's adaptability and efficiency. The destroy operators are detailed as follows:

- Random destroy. This operator randomly selects σ_1 users $p \in P_N(t)$ and removes them from the current matching solution. Here, σ_1 refers to the number of users selected for removal.
- Worst-profit destroy. This operator selects σ_2 vehicle-user matches and removes them from the solution, σ_2 represents the number of matches chosen specifically from those with the lowest profits.
- Dual destroy. This operator selects σ_3 pairs of vehicle-user matches, where the users in each pair can be exchanged between the vehicles, σ_3 denotes the number of such pairs selected for interchange.

The following repairs are designed to optimally rebuild the solution based on evaluations and strategic adjustments:

- High-probability repair. After the random destroy, this operator evaluates the possible alternatives for the removed users, where the alternative with the highest probability from C_p^H of the removed user p is reintroduced into the solution.
- High-profit Repair. Triggered by worst-profit destroy, this operator seeks out the most profitable alternative from C_p^H for removed users.
- Swap Repair. Following the dual destroy, this operator focuses on regenerating the matching by exchanging the alternatives between the pairs of users.

7. Experimental result

This section validates the proposed approach with the Beijing network and the ride-hailing service data provided by DiDi. To demonstrate the effectiveness of the approach, we assess the efficiency of the introduced ALNS method. We further evaluate the performance of the HCRS by comparing it with conventional car-based ride-splitting and ride-hailing and perform a sensitivity analysis of the incentive parameters to understand their impacts.

7.1. Experiment design

7.1.1. Dataset

This study examines ride-hailing service data sourced from DiDi, one of China's foremost transportation network providers. The dataset includes approximately 16.61 million trip records from DiDi Express orders, recorded between July 1, 2017, and July 30, 2017, covering the entirety of Beijing. Each record contains various attributes, including driver IDs, user IDs, fare, distance, start and end times, and pickup and drop-off coordinates.

7.1.2. User classification

Given the one month's travel records of Beijing, we hypothesise four user classes and group users based on the classification approach and analysis provided in Appendix 1. Each

Table 5. User classification and statistical indexes.

Class	Quantity	Ratio	ride-sharing ratio	Fare (shared)	Fare (solo)	IVT (shared)	IVT (solo)
1	68040	1.81%	33.46%	22.63	19.12	32.01	21.58
2	49404	1.31%	23.47%	17.95	21.02	26.67	23.37
3	1219495	32.46%	0.28%	24.83	25.22	31.26	25.59
4	2419498	64.42%	12.03%	19.40	23.70	27.99	25.17

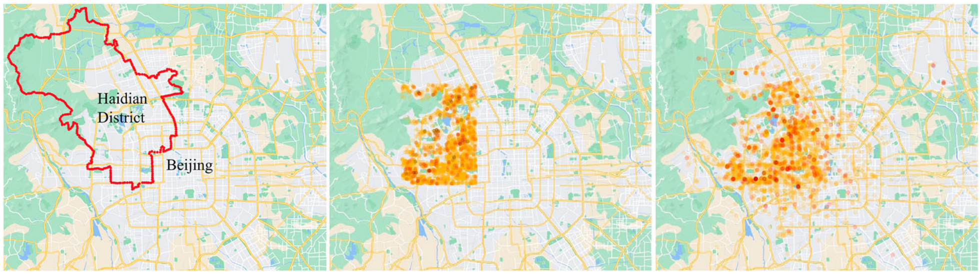

Figure 3. Study area: Haidian district of Beijing.

class reflects different sensitivities that affect their travel decisions. Additionally, we have enriched each record by indicating whether the trip is solo or shared and by detailing the IVT.

These four classes are defined: Class 1 consists of fare-sensitive users who favour shared rides. Class 2 includes users who prefer shared rides during peak times. Class 3 comprises users sensitive to the quality of service (QoS), particularly affected by the number of passengers sharing the ride. Class 4 encompasses users with a mix of travel behaviours, indicating varied influences on their travel choices. Table 5 categorises the users and distinguishes between shared and solo trips in the Beijing travel data. Detailed spatial-temporal distributions are provided in Appendix 1.

7.1.3. Scenario design

To evaluate the effectiveness of the introduced HCRS service, our study focuses on user requests originating from the Haidian district of Beijing, as depicted in Figure 3(a). Haidian is known for its concentration of educational and technological institutions, which significantly influences the local demand for shared services. For our analysis, we used travel data from July 3rd, 2017, a typical working day, including origins and destinations (ODs), and preferred departure and arrival times. While all requests originate in Haidian, the destinations may be located outside this district.

To explore the performance of our approach during different daily time frames, we defined three scenarios reflecting varied user demand patterns: morning peak (7:00–8:00, S1), evening peak (17:00–18:00, S2), and off-peak hours (13:00–14:00, S3). Each scenario captures a distinct pattern of user requests, influenced by Haidian's urban dynamics. Table 6 provides detailed information on the number of users, demand nodes, and percentages of users in different classes. Figure 3(b,c) illustrates the distribution of ODs for Scenario 1.

7.1.4. Parameter settings

Parameters of the network. We assume a homogeneous fleet of HCRS vehicles, each with a capacity of 8 people. The cost structure for these vehicles includes a fixed cost (c_f) of ¥15 and a travelling cost (c_d) of ¥1.6 per kilometer of each trip. As the lack of access to detailed

Table 6. Information of each scenario.

Scenario	Users(per)	Demand nodes	Class1	Class2	Class3	Class4
S1	10231	16572	3.32%	10.95%	62.12%	23.60%
S2	10269	16284	3.97%	7.34%	56.72%	31.97%
S3	7441	11667	2.69%	1.59%	56.11%	29.61%

Table 7. Parameters of choice model.

	Class 1	Class 2	Class 3	Class 4
Fare	−0.105	−0.042	−0.051	−0.065
Time	−0.087	−0.011	−0.034	−0.040
Comfort	−0.2			
Tolerable waiting time(min)	10	8	5	8
Tolerable detour distance(km)	5	3	1	3
Tolerable shared user(people)	8	6	4	6

traffic congestion data, here, we assume a constant travel speed of 20,25,and 30 (unit: km/h) for the three scenarios. Each demand node has a constant dwell time of 20 s.

In the given user choice model, the values of ASC^H, ASC^R are set as 0.727, 0.863 (Zhang et al. 2022). Here, the other mode is treated as taxi, where the utility is related to the travel time (tt_p) and fares (always higher than those of ride-hailing). The estimation of the user choice model is not the focus of this work, the class-based sensitivities to key factors and class-related mobility preferences are given in Table 7. Due to the lack of HCRS travel data, λ_n^H of HCRS nest is set to 0.669, referring to value estimated for shared services (Zhang et al. 2022). More details of the choice model parameter settings are given in Appendix 2.

The ride-hailing fare structure is defined with a constant fee (f_0) of ￥13. The distance and time rates (f_d, f_t) are 2￥/km and 0.6￥/min. The incentives ϵ_d and ϵ_e are set as 1￥/km and 0.58￥/kg. This rate is derived by multiplying the base emission value in Beijing (0.058￥/kg) by a factor of 10 to enhance the incentive. Other parameters are given below: $c_d = 1$￥/km.

Parameters of the ALNS. The iteration is set as 50. Initially, the weights and probabilities of all destroy-repair operators are the same, set as $w = 0$ and $prob = 1$. We conduct our experiments with Matlab 2019b and CPLEX 12.9 on a computer with a 3.4 GHz CPU and 16 GB of RAM.

7.2. Performance of solution approach

This section aims to evaluate the performance of the introduced matching approach (ALNS) in comparison with the exact algorithm provided by CPLEX. For the comparison, three small-scale instances, i.e. S1-1 (1600 requests), S2-1 (1973 requests), and S3-1 (1392 requests), are extracted from the S1, S2 and S3. Each instance represents a 10-min scenario where HCRS operations are updated every minute. Both ALNS and CPLEX are utilised for the matching process, while the rolling horizon and shared choice set generation remain same across both methods. The computational effort and objective value of the matching process are represented individually of each cycle (i.e. 1-min cycle). The total computational effort and total profit generated with both approaches are presented in the 'Total' column. The results are summarised in Table 8.

Table 8. Performance of ALNS (A.) and CPLEX (C.) for small-scale instances.

	Metric		Cycle 1	2	3	4	5	6	7	8	9	10	Total	Diff. (%)
S1-1	Time	*C.*	0.245	0.261	0.116	0.166	0.148	0.305	0.104	0.174	0.298	0.244	2.061	
	(sec)	*A.*	0.094	0.111	0.075	0.096	0.084	0.094	0.115	0.127	0.179	0.181	1.156	−43.91
	Obj.	*C.*	3667.82	2430.13	3094.57	3176.63	3369.16	2573.73	3874.16	5878.79	5950.54	7108.65	41124.18	
	(¥)	*A.*	3307.66	2523.58	2272.71	2971.88	2163.87	2736.97	3554.49	6885.67	4454.68	8875.52	39747.04	−3.35
S2-1	Time	*C.*	0.225	0.218	0.212	0.278	0.269	0.255	0.225	0.313	0.349	0.368	2.712	
	(sec)	*A.*	0.180	0.081	0.192	0.065	0.080	0.085	0.185	0.175	0.169	0.174	1.386	−48.89
	Obj.	*C.*	2722.39	2874.93	3286.35	4389.75	4540.52	4465.41	3391.65	3699.46	6405.16	7192.04	42967.66	
	(¥)	*A.*	2655.24	3079.96	3222.11	4555.88	4189.49	4493.29	3055.59	3545.05	5964.27	7357.29	42118.17	−1.98
S3-1	Time	*C.*	0.189	0.268	0.215	0.213	0.226	0.269	0.243	0.369	0.413	0.429	2.834	
	(sec)	*A.*	0.151	0.095	0.115	0.201	0.175	0.192	0.186	0.200	0.240	0.195	1.750	−38.25
	Obj.	*C.*	3090.12	3817.56	3602.33	3967.17	4257.75	4770.12	4517.56	5373.21	5999.0	4976.31	44371.13	
	(¥)	*A.*	2510.92	3721.52	3317.15	5007.48	4643.46	4612.42	3829.62	5875.39	5105.87	4804.15	43427.96	−2.13

The results of the study show that the ALNS is capable of generating solutions of comparable quality to those produced by CPLEX, with a minor average discrepancy of about 2.49%. However, a notable advantage of ALNS is its efficiency in terms of computational time, with an average reduction of 43.68% compared to CPLEX. Interestingly, ALNS produces higher profits than CPLEX in certain cycles (e.g. Cycle 6: ¥2736.97vs. ¥2573.73 in S1-1). This highlights ALNS's capability to occasionally generate more profitable results, which can be attributed to the different solutions produced by ALNS and CPLEX in earlier cycles. These differences influence the shared options and decisions available in following cycles, leading to variations in the outcomes.

These findings illustrate that ALNS is an efficient heuristic approach capable of delivering high-quality solutions within significantly shorter computational times compared to CPLEX. Its iterative process and flexibility allow it to occasionally identify more profitable solutions, which makes ALNS well-suited for dynamic transportation scenarios, offering rapid exploration of solution spaces and near-optimal results.

7.3. Performance of HCRS

7.3.1. HCRS vs. ride-splitting vs. ride-hailing

This section evaluates the performance of the HCRS in comparison with pure ride-hailing (RH) services. Additionally, we consider a ride-splitting (RS) solution involving cars with professional drivers. This comparison allows us to assess whether HCRS offers a superior alternative to standard car-based ride-sharing.

Operational improvement. Table 9 highlights the operational improvements of HCRS and RS compared to conventional RH, with percentages indicating the changes. HCRS demonstrates significant reductions in operating costs across all scenarios, with decreases exceeding 10.44%. RS also offers considerable savings, though with a slightly lower average reduction of 9.74%. In terms of profit, HCRS demonstrates notable improvements, especially during peak periods (S1, S2), with a significant peak in S1, showing a 19.37% increase compared to RH, while RS records a 12.68% increase. As for CO2 emissions, HCRS consistently delivers reductions, while RS leads less reduction, such as a 7.97% reduction in S3. These variations underscore HCRS's superior efficiency in matching and capacity utilisation, effectively serving multiple user classes and reducing environmental impact, particularly during high-demand periods.

Service level improvement. Table 10 provides a detailed comparison of service level enhancements by HCRS and RS over traditional RH, highlighting average changes in key

Table 9. Operational improvement of HCRS and ride-splitting (RS) over ride-hailing.

		Operational improvement (%)		
Scenario	Service	Operating cost	Profit	CO2
S1	HCRS	−10.44	19.37	−17.72
	RS	−8.94	12.68	−12.81
S2	HCRS	−13.85	18.29	−11.19
	RS	−11.29	12.67	−8.76
S3	HCRS	−11.51	15.26	−13.65
	RS	−9.00	9.74	−7.97

Table 10. Average service level improvement of HCRS and ride-splitting (RS) over ride-hailing.

Scenario	Service	Average service level improvement					
		Fare (¥)	WaitT (min)	Deviation (min)	Detour (km)	Share (people)	CO2 (kg)
S1	HCRS	−4.28	2.18	3.59	2.73	4.27	−3.84
	RS	−2.23	1.33	1.50	2.05	1.43	−1.71
S2	HCRS	−3.24	2.57	3.30	2.32	4.30	−4.12
	RS	−1.28	1.45	1.95	1.77	1.57	−1.16
S3	HCRS	−2.42	2.24	3.00	3.40	4.11	−2.52
	RS	−1.58	1.85	1.81	1.53	1.57	−1.59

performance metrics such as fare, waiting time (WaitT), schedule deviation (Deviation), detour distance (Detour), number of shared users (Share), and CO2 emissions. HCRS outperforms RS in reducing fares (with an average reduction of ¥3.31) and CO2 emissions (decreasing from 2.52 to 4.12 kg) compared to RH. These results indicate that HCRS is more effective in vehicle allocation, offering greater incentives, and achieving lower emissions through increased sharing, as evidenced by the average shared user count exceeding 4.11 people across all scenarios. However, the trade-offs for HCRS include slightly longer waiting times, more significant schedule deviations, and additional detours due to accommodating more users and navigating more complex routes, which can lead to delays in pickup and delivery.

Discussion of ride-splitting. Although RS provides certain advantages over RH, it faces notable challenges when compared to HCRS, as RS leads to a slight reduction in CO2 emissions by 1.16 kg. Moreover, while RS does improve service levels compared to RH by reducing fares, lowering environmental impact, and increasing shared rides, it still falls short of the superior benchmarks established by HCRS.

7.3.2. Service enhancements for user classes

This section details the service level enhancements delivered by a hypothetical HCRS system across all scenarios for the studied four user classes.

Average service level improvements. Table 11 highlights distinct service enhancements for each user class within the HCRS framework compared to RH, showcasing their varied priorities and the trade-offs involved. **Fare-sensitive users** (Class 1) see the most significant fare reductions, particularly in S1 and S2 with 4.74 and 3.68 (unit:¥), but encounter longer detours, reflecting a compromise between cost and convenience. **Access- and QoS-sensitive users** (Classes 2 and 3) enjoy fewer detours, with prioritised direct routes. Class 3, in particular, enjoys the most efficient services in deviations tailored to those who prioritise speed and quality. Despite these complexities, all user classes benefit from CO2 emission reductions beyond 2.18 kg, especially during the evening peak, demonstrating the environmental advantages of efficient ride-sharing.

Detailed variations. Figures 4-5 present the detailed variations in fare savings and emission reductions. In Figure 4, all classes exhibit greater variability in S1 and S2, while show fewer variations in S3. Notable outliers across all classes indicate higher savings for certain users. In Figure 5, all classes exhibit significant variability and outliers, particularly during the evening scenario (S2). These variations are influenced by differences in traffic conditions, demand levels, and diverse routing needs, leading to fluctuating values.

Table 11. Average service level improvement of HCRS compared to ride-hailing (RH) of Fare-sensitive (Class 1). Access-sensitive (Class 2), QoS-sensitive (Class 3) and Mixed (Class 4) user classes.

		Average service level improvement					
Scenario	Class	Fare (¥)	WaitT (min)	Deviation (min)	Detour (km)	Share (people)	CO2 (kg)
S1	1	−4.74	2.10	2.94	3.79	4.08	−3.45
	2	−4.68	2.67	3.27	2.93	4.41	−3.89
	3	−3.60	1.48	2.72	2.49	4.24	−3.79
	4	−3.69	2.67	3.85	2.27	4.54	−3.92
S2	1	−3.68	2.67	3.37	2.33	4.51	−4.89
	2	−3.13	2.34	2.64	2.06	3.97	−3.70
	3	−3.33	2.15	2.67	2.31	4.14	−3.93
	4	−3.47	2.70	4.12	2.43	4.90	−3.83
S3	1	−2.60	2.48	2.72	3.49	4.24	−2.79
	2	−2.35	2.58	3.47	3.41	4.03	−3.06
	3	−2.29	3.26	2.26	2.45	4.74	−3.71
	4	−2.51	1.56	3.31	2.81	4.05	−2.18

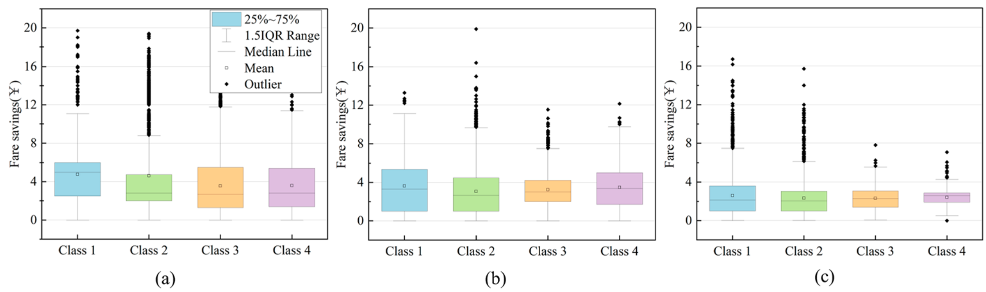

Figure 4. Fare savings of different user classes in S1 (a), S2 (b) and S3 (c).

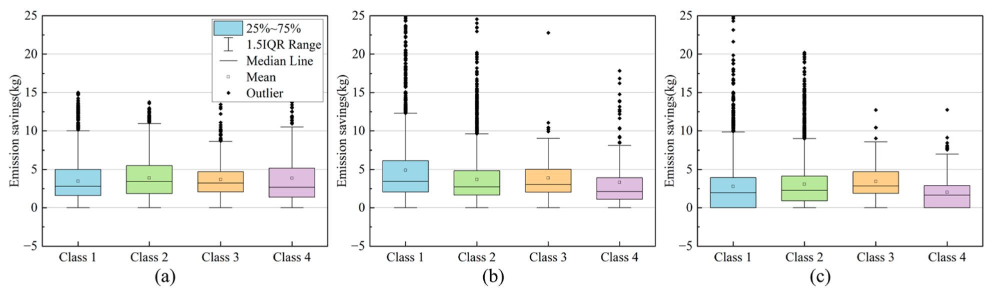

Figure 5. Emission reductions of different user classes in S1 (a), S2 (b) and S3 (c).

7.3.3. Performance on long and short trips

Shared rides may provide enhanced service levels on longer trips, driven by specific incentives. This section investigates the performance of HCRS across various distances to assess where they are most beneficial. Additionally, we explore ride-splitting, which serves as an alternative shared option.

Table 12 provides a detailed comparison of average values for HCRS and RS over RH across scenarios, where short-distance is defined as those less than 10 km. HCRS and RS provide more significant fare savings on long trips compared to short ones across various

Table 12. Average service level improvements of HCRS and ride-splitting (RS) over ride-hailing (RH) for long-distance (L) and short-distance (S) trips.

			Average service level improvement					
Scenario	Service	Trip	Fare (¥)	WaitT (min)	Deviation (min)	Detour (km)	Share (people)	Co2 (kg)
S1	HCRS	L	−4.94	2.81	3.74	3.18	4.28	−4.29
		S	−3.68	1.21	2.45	1.56	4.25	−2.19
	RS	L	−2.85	1.47	1.65	2.65	1.44	−2.24
		S	−1.90	1.07	0.98	1.01	1.41	−1.19
S2	HCRS	L	−3.61	2.75	3.84	2.36	4.73	−4.29
		S	−2.29	1.87	2.45	2.26	3.72	−2.72
	RS	L	−1.93	1.49	1.92	1.81	1.86	−1.58
		S	−1.15	1.11	2.00	1.40	1.26	−0.85
S3	HCRS	L	−2.51	2.39	3.33	3.65	5.10	−2.54
		S	−2.16	1.93	2.80	2.78	3.67	−1.86
	RS	L	−2.11	1.85	1.96	1.83	1.56	−2.16
		S	−1.07	1.84	1.38	1.49	1.58	−1.05

scenarios. For example, in S1, long trips see fare reductions of 4.94 and 2.85, while short trips reduce by 3.68 and 1.90 (unit: ¥), respectively. Additionally, long trips typically yield higher CO2 savings and greater share participation, with HCRS notably achieving 4 shared users and a 4.29 kg CO2 reduction in S1. However, these benefits come at the cost of delays, especially for short trips. Also, the extensive deviations and detours required for long trips indicate the need for complex routing to maximise vehicle utilisation. Overall, these patterns underscore that shared rides, particularly HCRS, are more advantageous over longer trips, enhancing routing efficiency and reducing environmental impacts. The challenges with shorter trips highlight the difficulties in effectively integrating them into shared ride systems.

7.4. Sensitivity analysis

This section examines the effects of varying the incentive parameters regarding distance (ϵ_d) and emission reductions (ϵ_e). The initial settings are $\epsilon_d = 1$¥/km and $\epsilon_e = 0.58$¥/kg. To explore how these incentives influence service attractiveness and user choices, we modify each parameter by ¥50%, resulting in $\epsilon_d^+ = 1.5$¥/km, $\epsilon_d^- = 0.5$¥/km, $\epsilon_e^+ = 0.87$¥/kg, and $\epsilon_e^- = 0.29$¥/kg.

Operational and behavioural responses to incentive changes. Table 13 details the effects of modifying the incentive parameters ϵ_d and ϵ_e to baseline levels. Increasing ϵ_d results in

Table 13. Impact of incentive parameters on operational and service metrics relative to baseline in S1.

Category	Metric	ϵ_d^+	ϵ_d^-	ϵ_e^+	ϵ_e^-
Operation	Profit(¥)	−1236.44	1078.95	−3245.43	2034.38
	Operating cost(¥)	−376.34	245.38	−227.52	453.69
	CO2(kg)	−594.33	261.56	−440.47	381.52
Service level	$f^R - f^*$(¥)	0.37	−0.41	0.44	−0.56
	$f^* - \hat{f}$(¥)	0.38	−0.19	0.23	−0.39
	Probability	0.23%	−0.18%	0.26%	−0.21%
	Share(people)	−0.26	−0.13	−0.12	−0.11

Note: $f^R - f^*$ and $f^* - \hat{f}$ represent the average fare savings of HCRS compared to RH, and the savings between the final and preliminary fares of HCRS, respectively. 'Probability' indicates the percentage of users opting for shared trips.

Table 14. Impact of incentive parameters on user fares and choices across different classes in S1.

Class	Metric	ϵ_d^+	ϵ_d^-	ϵ_e^+	ϵ_e^-
1	$f^* - \hat{f}$(¥)	0.48	−0.22	0.31	−0.42
	Probability	0.24%	−0.25%	0.33%	−0.28%
2	$f^* - \hat{f}$(¥)	0.43	−0.21	0.25	−0.37
	Probability	−0.11%	−0.25%	−0.14%	−0.25%
3	$f^* - \hat{f}$(¥)	0.22	−0.14	0.23	−0.35
	Probability	0.22%	−0.08%	0.23%	−0.18%
4	$f^* - \hat{f}$(¥)	0.33	−0.11	0.18	−0.21
	Probability	−0.06%	−0.15%	0.25%	−0.17%

reduced profit (¥1236.44), operating costs (¥376.34), and emissions (594.33 kg), suggesting that service utilisation rates encouraged by higher incentives may not be financially feasible due to insufficient fare revenue. Conversely, decreasing ϵ_d enhances profit and operational efficiency. Similar trends are observed with changes in ϵ_e. Higher incentives can lead to fare savings and may enhance the appeal of HCRS, but they also tend to reduce the likelihood of users opting for shared rides and decrease the number of users sharing a trip. This highlights the intricate impact that incentive changes can have on user behaviour.

Behavioral analysis of different user classes. Table 14 analyzes user behaviour across different classes based on average fare savings ($f^* - \hat{f}$) and the likelihood of opting for shared options. Fare-sensitive users (Class 1) react strongly to increased incentives, achieving the highest fare savings (¥0.48 for ϵ_d^+ and ¥0.31 for ϵ_e^+) and showing the largest positive change in choosing shared rides, underscoring their price sensitivity. In contrast, Mixed users (Class 4) exhibit less price sensitivity (−0.11 and −0.21, unit:¥) and a slight decrease in shared ride usage under reduced incentives. Access-sensitive and QoS-sensitive users (Classes 2 and 3) demonstrate moderate fare sensitivity with varied responses to incentive changes, reflecting a balance of fare concerns and other service attributes. Overall, adjusting incentive parameters significantly impacts operational efficiency, profitability, environmental sustainability, and user behaviour, and Fare-sensitive users display high price elasticity.

8. Conclusion

This study introduces a high-capacity ride-sharing (HCRS) system designed to strategically incorporate user choice decisions and dynamic pricing schemes to tackle the complexities of the dynamic HCRS operation. The dynamic ride-sharing problem integrates the nested logit choice model and dynamic fare adjustment strategies. A rolling horizon approach is employed to solve this problem, utilising a shared choice set generation algorithm and an ALNS-based matching algorithm.

Numerical experiments were conducted to evaluate the effectiveness of the proposed framework, using ride-hailing data from Beijing for user classification and choice model estimation. The experiments revealed that the HCRS significantly outperforms traditional ride-hailing and ride-splitting in terms of profitability and environmental impact, achieving up to an 21.16% reduction in CO2 emissions and a 22.75% increase in profits. User experiences vary greatly across different user classes, with peak hours presenting opportunities for fare and emission savings but also risks of longer detours and increased waiting times. Additionally, a sensitivity analysis of incentive parameters uncovers varying fare elasticity among different user classes. These insights offer valuable guidance for discussions on sustainable high-capacity shared mobility and provide practical advice for TNCs.

In future research, we plan to expand upon the current framework by integrating the latent class choice model, and it is interesting to examine the impact of varying thresholds of user classification on system performance. Furthermore, we intend to explore the optimisation-based pricing, and incorporate group bookings and user relationships in the modelling framework.

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Appendices

Appendix 1. User classification analysis

A.1. Shared ride recognition

Due to the lack of explicit ride-sharing indicators within the given dataset, we apply a methodology to distinguish between solo and shared rides as follows: (i) the orders are first organised by Driver ID and sorted chronologically; (ii) each consecutive pair of orders is analysed for a temporal overlap of at least three minutes, identifying such overlaps as indicative of ride-sharing; (iii) a 'ride-sharing indicator' is introduced to the dataset, where a value of 0 signifies a solo-passenger trip and 1 signifies a shared trip.

A.2. Classification criteria

Previous empirical studies indicate that user heterogeneity of sharing motivations play a critical role in influencing whether travellers are willing to utilise ride-splitting (Lavieri and Bhat 2019; Morris

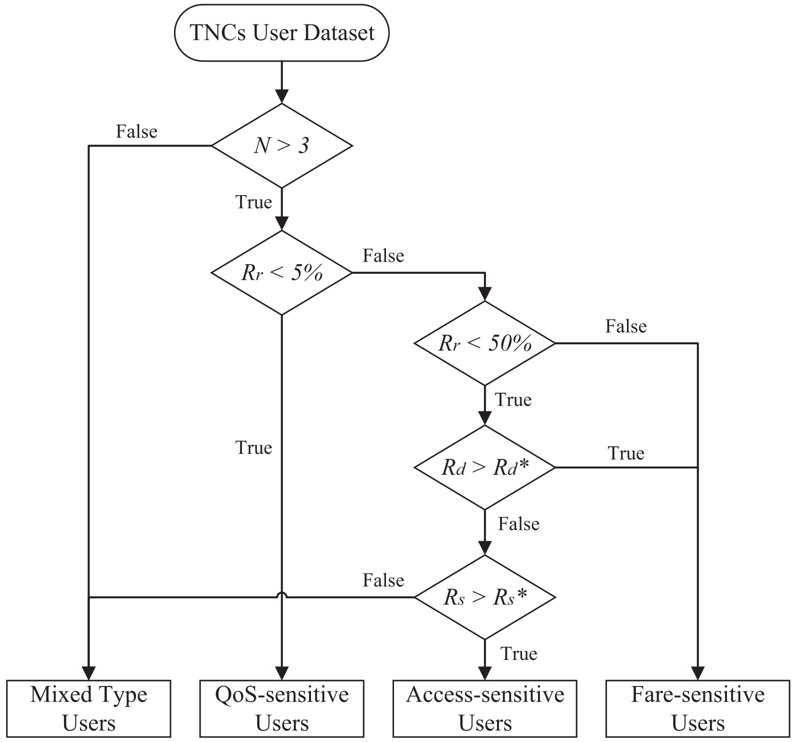

Figure A1. User classification process.

et al. 2019; Taiebat, Amini, and Xu 2022). Some scholars argue that people with high demands for safety, comfort, and privacy, particularly women, exhibit higher requirements for service quality and perceived cost. Consequently, these individuals are less frequent to opt for ride-splitting (Morris et al. 2019; Sarriera et al. 2017). Additionally, Huang et al. (2023) identify the time-fare trade-off as the most critical factor determining the sharing willing of ride-sourcing users. These studies reveal that different users may have various sharing motivations, being sensitive for such as service quality, cost-savings or time-savings, which provides valuable insights for identifying different user groups of ride-hailing services.

Here, we construct a user classification system that categorises users into four groups: QoS-sensitive Users, Fare-sensitive Users, Access-sensitive Users and Mixed Type Users. We assume that QoS-sensitive Users seldom choose ride-splitting, likely due to higher demands for quality and perceived cost of travel. Fare-sensitive Users predominantly opt for ride-splitting because of lower cost, as a consequence of which, these users may have a high ride-splitting frequency and longer trip distance. Access-sensitive Users prioritise the reliability of their trips such as arrival time and waiting time, who are more inclined to use ride-splitting during difficult to-call scenarios, e.g. peak hours or adverse weather. Mixed Type Users are difficult to classify accurately due to various constraints. According to the travel patterns of different users in above assumptions, we consider key factors of individual sharing frequency, distance, and scenarios, in this user classification system and the specific steps are as follows.

This section outlines the detailed approach used for classification (see Figure A1, with key factors of shared frequency, trip distance and adoption scenarios. Massive order data with user ID and weather conditions are extracted to define these classification criteria.

First, we categorise users with relatively fewer monthly trips as Mixed users, with a threshold of 3. Second, users with a ride-splitting adoption frequency under 5% are classified as low-frequency sharing users and labelled as QoS-sensitive users. Conversely, users who participate in sharing more than

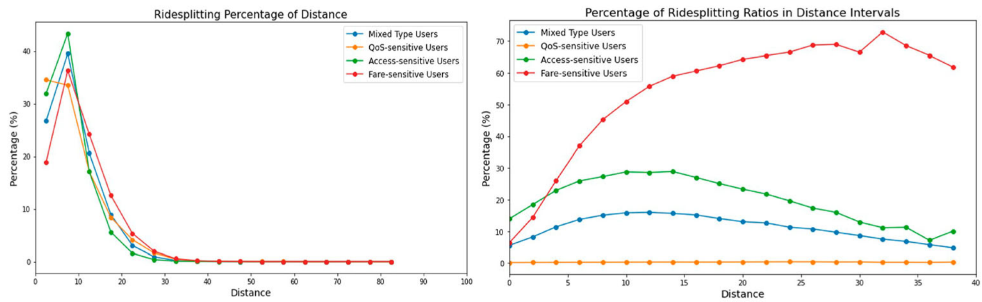

Figure A2. Travel distances distribution (a) and trip ratios by distance intervals (b) across four user classes.

50% of the trips are categorised as high-frequency ride-sharing users, termed as Fare-sensitive users. To further classify the rest of medium-frequency ride-sharing users, we compare their travel distance and using scenarios between shared trips and solo trips. Users are categorised as Fare-sensitive if their average travel distance by ride-splitting is much higher than the average travel distance by solo ride-hailing. Users are categorised as Access-sensitive if most of their shared trips are during peak hours or adverse weather. The rest of medium-frequency ride-sharing users are divided into Mixed type.

The parameters in the flowchart are as follows: N: the number of trips per user, here is 3. R_r: ride-splitting trip ratio, i.e. the proportion of shared trips to total trips for a user R_d: long-distance trip ratio, i.e. the ratio of the average distance of shared trips to the average distance of solo trips for a user. R_d^*: the threshold of R_d, here is 200%. R_s: special-scenario trip ratio, i.e. the ratio of the number of shared trips for special scenarios to the total shared number of trips for a user. R_s^*: the threshold of R_s, here is 50%.

A.3. Spatio-temporal features of user classes

Figures A2-A3 illustrate the distance and temporal distributions for various user classes. Travel data shows that most users' trips peak within the 5–10 km range, except for QoS-sensitive users who favour shorter trips, likely due to their higher service quality expectations. Conversely, Fare-sensitive users often choose medium- to long-distance shared rides to economise, in contrast to their shorter solo trips. Figure A2 highlights differing ride-sharing ratios across distances, with Fare-sensitive users showing a distinct preference for longer shared trips to save costs, while QoS-sensitive users exhibit consistently low sharing ratios. Temporal analysis in Figure A3 indicates that Fare-sensitive and Access-sensitive users primarily opt for shared rides during weekday peak hours, with a noticeable drop in activity over weekends, reflecting their distinct preferences shaped by cost considerations and commute times.

Appendix 2. User choice model parameter setting

Even though various user classes and their corresponding choice models have been examined, the specific user classes and user choice model for high-capacity shared mobility in Beijing remains unexplored. This gap in research complicates the determination of class-based utility coefficients described in Equations (5)-(6).

To address this, we have developed a binary logit model aimed at analyzing the ride-sharing decision-making processes among four different TNC user categories. Our methodology involved the following steps: (i) we segmented the area within the Fifth Ring Road of Beijing into 1 km × 1 km cells, creating a total of 336 grids (16 × 21); (ii) we mapped the DiDi order data onto these grids using passenger location information, thus generating grid-level data. The likelihood of choosing ride-sharing is quantified by the ratio of ride-sharing trips to total trips for each origin-destination (OD) pair. For the independent variables, we calculate the average total fee, and In-Vehicle Time for both sharing

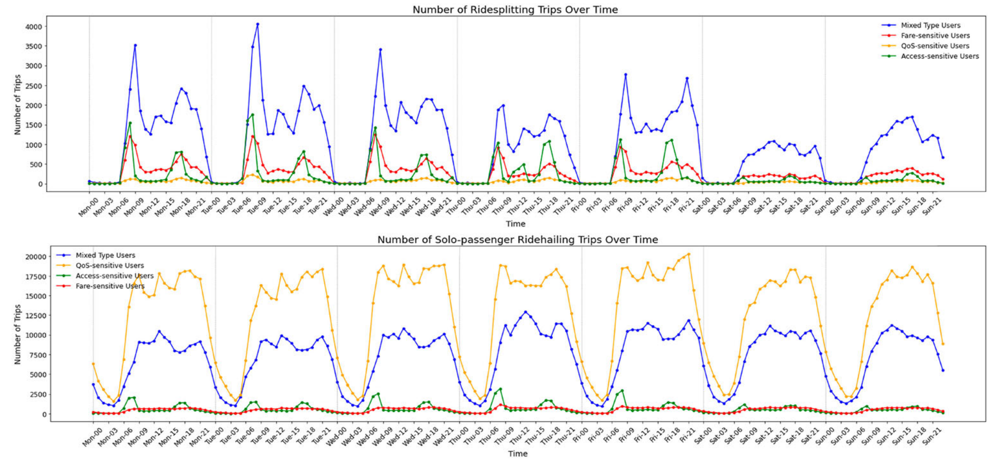

Figure A3. The temporal distribution of ride-sharing trips and solo-passenger ride-hailing trips.

Table A1. Class-based parameters.

	Class 1		Class 2		Class 3		Class 4	
	Est.	T-stat	Est.	T-stat	Est.	T-stat	Est.	T-stat
Fare	−.105	−9.955∗	−.042	−9.990∗	−.051	−18.637∗	−.065	−21.749∗
TT	−.087	−8.164∗	−.011	−3.072∗	−.034	−12.183∗	−.040	−10.254∗
	R^2: 0.173		R^2: 0.145		R^2: 0.160		R^2: 0.121	

Note: ∗ Statically significantly at 5% significance level

and solo trips For the choice model estimation, the maximum likelihood estimation (MLE) is applied through SPSS. The estimation is given in Table A1. As there is no shared in-vehicle data, here, we set β_f^c is 0.2 to all classes, referring to Liu et al. (2020).

It is important to note that our estimated parameters can capture sensitivities of TNC users in Beijing to traditional car-based ride-sharing. However, due to a lack of specific data for HCRS, the applicability of parameters to HCRS service is limited. This data gap may prevent the estimated coefficients from capturing all the nuances of individual choice dynamics, which needs further exploration in the future work.