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Quantifying the potential benefits of buspooling: Case study and sensitivity analysis☆

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ABSTRACT

In the realm of mobility services, high-capacity ridesharing such as buspooling holds promise in alleviating the overuse of low-capacity cars and addressing accessibility bottlenecks to public transit systems. However, research on buspooling remains in its fancy stage, requiring dedicated efforts to quantify and enhance its potential benefits. In this paper, we propose car-user-oriented and sustainable operating principles and embody them in a passenger matching model. Furthermore, we employ a solution approach including the spatial-temporal pruning strategies and a heuristic algorithm to guarantee the efficiency of larger-scale computing. Applying this system to the case of Beijing, results demonstrate that buspooling services could yield significant benefits to passengers, operators, and the environment. The consistency observed between the distribution of taxi trips and bus routes suggests that buspooling could effectively enhance subway accessibility, especially for residents in suburban areas. Moreover, findings from a sophisticated analysis can inform the design of a more attractive and eco-friendly system for intermodal transit services in practice.

1. Introduction

In recent years, the widespread adoption of the mobile internet and the emergence of the sharing economy have given rise to a variety of ridesharing services. These include car-based ridesharing (CRS), like ride-splitting and carpooling, and high-capacity ridesharing (HCRS), like buspooling and customized buses, offering different fare levels (FLs) and vehicle capacities (VCs), as illustrated in Fig. 1. Among these, CRS has emerged as the dominant mode in the ridesharing service market, which is recognized as a means of reducing the number of cars, congestion, and pollution by sharing empty seats (Liu et al., 2019; Santi et al., 2014; Tikoudis et al., 2021). Given the issues of low capacity and high fare, however, CRS is not friendly enough for low-income groups and fails to satisfy the highly spatial-temporal concentrated travel demand, like first/last-mile access to subway-intensive metropolitan areas during rush hours (Agatz et al., 2012).

To address this challenge, some public transport agencies in megacities introduce the customized bus (CB) into current public transit system, which is more affordable and eco-efficient than CRS, and more flexible than conventional bus (Lee & Savelsbergh, 2017; Shang et al., 2022). However, CB are typically designed for general travelers and may exhibit limitations in service quality, such as detours and discomfort due to multiple stops, as well as delays in route and schedule updates, thereby reducing their appeal to car users. Meanwhile, some transportation network companies (TNCs), e.g. DiDi in China, have launched an on-demand HCRS, buspooling, into the mobility service market. Compared with the CB, the mobile-internet-based buspooling primarily caters to car commuters, offering one-stop mobility services more flexibly. Users submit their requests via TNCs mobile applications in advance, after which the platform groups requests with similar itineraries and assigns vans or minibuses to accommodate these passengers.

Focusing on the emerging and eco-friendly buspooling service, this

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work has two goals. The first one is to quantify the potential benefits of buspooling in practice. Although sounds like an appealing concept, buspooling is still in its nascent stage of development. Indeed, the specific benefits of buspooling on a large scale remain somewhat unclear, particularly for cities in developing countries (Alonso-Mora et al., 2017; Liu & Liu, 2020). The second goal is to further enhance the benefits of buspooling by addressing following key operation issues. The first is how to design an attractive transport system with on-demand ability, which is hard to be achieved without understanding the individual preferences of potential users based on empirical trip data (García-Melero et al., 2022; Zhan et al., 2022). Second, a high-efficiency solution algorithm is necessary to meet people's intensive demand for real-time mobility services, especially in large-scale metropolitan areas (Alonso-Mora et al., 2017; Zuo et al., 2021). Lastly, more effective operation strategies and promotion policies should be proposed and examined in buspooling system (Stiglic et al., 2018).

In order to quantify and enhance the potential benefits of buspooling, especially for the first/last-mile access to subway stations, we propose specific user operating principles and embody them in a passenger matching model. Moreover, spatial-temporal pruning strategies and a heuristic algorithm are employed to guarantee the solution efficiency. Applying this buspooling system to the case of Beijing, the matching performance of the proposed model is examined and promotion strategies for this system are discussed. The main contributions of this paper can be summarized as follows.

First, we formulate the buspooling matching model for car users as a mixed-integer linear programming (MILP) problem with an objective function comprising vehicle travel distance savings and operational revenue.

Second, we propose an efficient solution approach for larger-scale passenger matching problem, including the feasible trip set searching and passenger-vehicle interaction process, a similar line-merging method and a heuristic algorithm based on the scale of feasible passenger groups.

Third, taking the empirical taxi-trip access to subway stations as a proxy for individual demand of car users, we quantify the potential benefits of buspooling and compare the matching performance of buspooling connecting with various subway stations.

Fourth, we investigate the sensitivity of the matching model, considering the impact of participant preferences and operating strategies, to provide valuable insights on developing more attractive and beneficial HCRS matching system.

Note the user acceptability is one of the most crucial factors for the success of the proposed buspooling services. Although we seek to design an attractive ridesharing mode considering user preference and trip cost-savings, some qualified participants may still prefer private rides due to discomfort with sharing or other reasons. Focusing on this challenge, we would investigate the impact of varying participant rates on buspooling matching performance, and offer research conclusions and policy recommendations in a prudent manner.

The remainder of the paper is structured as follows. In Section 2, we present a literature review focusing on the ridesharing service mode, matching models and practical promotion issues. In Section 3, we detail the methodology of the on-demand matching system for buspooling. Our analysis of the Beijing metropolitan area dataset and the results of a series of experiments based on our model are discussed in Section 4. Finally, Section 5 completes this paper with major conclusions, as well as a discussion of future research.

2. Literature review

2.1. Ridesharing service modes

Ridesharing refers to a travel mode in which two or more groups of passengers with similar travel demands share the same vehicle to reach their respective destinations. Furuhata et al. (2013) classified ridesharing services into two categories: organized and unorganized. The former mainly refers to a travel service, frequently provided by a company, to facilitate trip sharing among passengers unknown to each other, while the latter is spontaneous ridesharing among family members, colleagues and other acquaintances. Thanks to the development of advanced information technology, many TNCs provide passengers with App-based ridesharing services, and the online mobility service modes have become more diversified, including those such as private-car-based carpooling, car-hailing-based ridesplitting, van-based vanpooling and bus-based ridesharing, like buspooling and customized bus.

Private-car-based carpooling involves a private car owner and passengers, where the car owner has his or her own travel needs and shares the trip as a driver to save on costs, often with the primary purpose of commuting (Chen et al., 2019; Schreieck et al., 2016). Private-car-based carpooling can be further categorized into four types, namely, single driver and single passenger, single driver and multiple passengers, multiple drivers and single passenger, and multiple drivers and multiple passengers (Agatz et al., 2012; Lu et al., 2020). At present, the most commonly used mode is the first one, where a private car owner picks up and drops off only one group of passengers. Popular private-car-based carpooling service platforms around the world include DiDi Hitch, Waze, Blablacar, etc.

Ridesplitting is the sharing of trips between passengers who are strangers, where the drivers are professionals who do not need to travel. The drivers pick up and drop off passengers according to the passengers' designated locations (Lokhandwala & Cai, 2018, Yan et al., 2019). Anticipatory assignment of customers to meeting points is another method to improve the system environment benefits (Dieter et al., 2023). The travel purposes of online ridesplitting passengers are diverse and not limited to commuting. Dominant car-hailing-based ridesplitting service platforms include DiDi Express, Uberpool, Lyft and so on.

Vanpooling and buspooling also occur between passengers, where

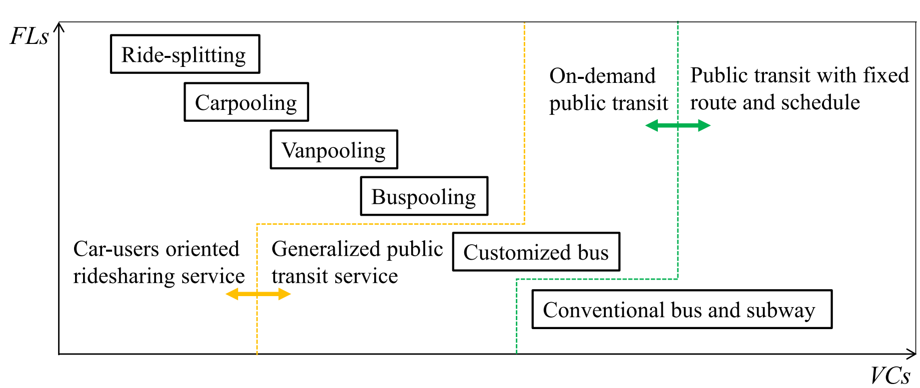


Fig. 1. The relationship between the vehicle capacities and fare levels of car ridesharing, bus ridesharing and conventional public transport.

the drivers are employed and do not have travel needs themselves. The maximum capacity of passenger sharing a van is usually 7, less than the capacity of minibus for buspooling (Huang et al., 2020; Liu & Liu, 2020). Although buspooling and customized buses can be both regarded as HCRS services, compared with customized buses, buspooling has some distinctions in terms of the operating mechanisms, service levels, etc. First, buspooling frequently have no or few intermediate stops on the route, so passengers can enjoy express mobility services similar to those of private cars or taxis. Second, in the operating process, these HCRS services set up schedules and routes only based on passenger travel demand at real-time. In contrast, customized buses can adjust their fixed schedules and routes according to individual travel demand, but the updates tend to lag behind and their demand-responsiveness is limited (Liu & Ceder, 2015; Wang et al., 2020). The specific differences between buspooling and other bus services are summarized in Table 1.

2.2. Passenger matching models and solution algorithm for high-capacity ridesharing

The passenger matching problem (PMP) for ridesharing services concerns which passengers can be grouped to share which vehicles under certain operational objectives. Compared with the passenger-matching models for CRS, HCRS needs to deal with a higher number of people sharing and more sharing combinations, therefore, the associated matching model and computation solution are more complex. There are limited studies of urban scale that quantify the benefits HCRS, mainly due to the lack of efficient and scalable algorithms for this problem (Alonso-Mora et al., 2017).

Compared with the rich literature on customized bus, the theoretical research on the HCRS matching model is in initial stages. Liu and Liu (2020) set up an optimization model to solve the buspooling matching problem with the objective of minimizing the total passenger road mileage, with the constraints of the passenger time window, bus capacity and route distance. Peng et al. (2021) developed an optimization model to solve a freight-passenger transportation integration problem for connecting buspooling with a train station. They considered the bus route detouring distance, passenger waiting time and load capacity, besides other common constraints. Evans IV and Pratt (2005) first provided an academic overview of the operational characteristics, practical examples and policy recommendations pertaining to vanpooling and buspooling services. However, this report did not delve into a comprehensive modeling analysis of operational challenges.

Considering the differences between buspooling and customized buses, some points need to be noted during modeling and solution process of buspooling. First, due to there being more stops on a bus line, most studies on customized buses have embedded the passenger matching into the vehicle routing problem (VRP) (Chen et al., 2021; Guo et al., 2019), and in this way the potential passenger combinations can be obtained through the solution of the optimal vehicle routing (Li, Hua, & Huang, 2018; Li, Song, et al., 2018). Nevertheless, buspooling should provide one-stop and express services to potential car users, such that the focus is not on vehicle route planning but on passenger matching. Moreover, buspooling services are car-user oriented, with a higher service level and limited use of public property. Hence, the operating companies will pursue a certain amount of ticket revenue. The objective function for customized buses, however, is mostly oriented towards reducing the total distance of the routes and matching more passengers, with little consideration of operating profits (Shen et al., 2021; Tong et al., 2017). Last but not the least, when addressing HCRS problem is the need to explore a very large decision space, while computing solutions fast enough to provide users with the experience of real-time booking and service. In order to meet the on-demand requirements, constraints such as pick-up and drop-off time windows are often considered in the HCRS optimization model (Chen et al., 2021; Guo et al., 2019). An efficient algorithm balancing computing time and accuracy is necessary for buspooling, especially for large-scale travel demand in metropolitan areas. Typical studies on passenger-matching models and solution algorithm for HCRS are reviewed in **Table 2.**

Table 1
Comparison of service features between buspooling and other bus services.

Service features	Traditional bus	Customized bus	Buspooling
Route	Fixed	Periodic update	On-demand
Stop	Fixed	Periodic update	On-demand
Schedule	Fixed	Periodic update	On-demand
Intermediate stops	Many	Some	None or few
Seats	Non-guaranteed	Guaranteed	Guaranteed
Passenger capacity	Larger	medium	smaller
Service object	General public	Commuters	Car commuters
Usage mode	Waiting at the stop	Online appointment	Online appointment

2.3. Key issues in enhancing the benefits of ridesharing

Although the HCRS can be conducive to alleviating urban traffic problems, the application on this mobility services remains in early stage, facing many challenges in its operational management. To address the accessibility bottleneck of subway and further amplify the environment benefits of ridesharing, scholars have considered the following aspects.

1) Paying more attention to the individual preferences of users to attract them to participate in HCRS. Thao et al. (2021), for example, focused on the preferences of potential users, particularly on the provision of information on the ridesharing scheme and affordability. Azadeh et al. (2022) considered user choices of transportation modes, implicitly incorporated in a mixed-integer linear problem, which enhances operational efficiency and service levels for multimodal mobility services.

2) Developing more effective promotion strategies. A range of scholars have designed various promotional strategies to enhance the integration of ridesharing and public transit: (a) Improving service quality. Ma et al. (2018) argued that a private on-demand mobility service operator might provide various options, including door-to-door passenger drop-offs, committing to dropping off or picking up at transit stations, or facilitating pick-ups and drop-offs at two different stations using different vehicles. Thao et al. (2021) adopted several crucial approaches to facilitate the integration of ridesharing with public transit. These included providing information on ridesharing schemes, incorporating ridesharing notice boards into local bus stops and regional railway stations, and employing pricing strategies to signify a contractual relationship between riders and drivers while reducing potential competition. (b) Strengthening support from both public and private parties. Stiglic et al. (2018) suggested that public transit providers might choose to collaborate with other stakeholders and offer additional benefits to drivers willing to accommodate riders. Such benefits could take the form of free park-and-ride tickets, toll waivers, High Occupancy Vehicle (HOV) lane permits, or priority parking in city centers. (c) Making moderate incentive policies. Zhang and Zhang (2018) identified a positive relationship between the use of public transit and ridesharing. This finding allows governments and transit operators to make informed decisions regarding subsidies on this new feeder service, without infringing on the interests of the public transport system is also an important topic. These studies have collectively sought to provide valuable insights for improving ridesharing service level and market share.

In conclusion, to quantify and further amplify the potential benefits of HCRS, there are still a lot work needs to do, including but not limited to proposing more attractive passenger-matching mechanism, more efficient solution algorithm and effective promoting strategies, in modeling of the buspooling system.

Table 2
Typical research on passenger-matching models for high-capacity ridesharing.

Author	Research object	Generalized trip cost	Schedule and route planning	Optimization objectives	Solution algorithm
Shen et al.	Customized bus	Passengers' waiting time and travel cost	Based on a real-life dataset	Improving accuracy of the real-time customized bus routes	H-R bilateral matching algorithm
Tong et al.	Customized bus	Passengers' space-time constraints	Based on a real case study	Optimizing the utilization of the vehicle capacity	Lagrangian decomposition
Kaan et al.	Vanpooling	Capacity of each van and travel time	Based on actual data	Minimizing total cost	The restricted allowance heuristic algorithm
Peng et al.	Buspooling	Fairness, waiting time, walking distance and time span	Based on real-life data	Enhancing fairness	Large neighborhood search heuristic algorithm
Liu et al.	Buspooling	Walking distance of passengers	Based on a real case study	Maximizing the ridesharing success rate	A dynamic grid-based heuristic algorithm

3. Methodology

3.1. Problem description

In this paper, a mobile-internet-based buspooling platform is introduced to guarantee on-demand matching between passengers and vehicles. This online system can provide necessary information to the passenger-matching model and an executor so that specific sensitivity analysis can be conducted. To attract more car users to shift to buspooling, we need to pay close attention to the travel habits and choices of passengers when modeling the matching process. It is necessary to clarify the following service principles:

- **Car-user-oriented: a) On-demand.** Rather than planning fixed routes and timetables like with conventional buses, the operational information for buspooling services is mainly determined from the travel demand distribution of potential passengers. **b) Express route.** To improve the travel experience and reduce the station dwell time, it is necessary to have no or as few as possible intermediate stations on a single buspooling line. **c) Real-time**. A high-efficient solution algorithm is necessary to meet the candidates' requirements for real-time mobility services.
- **Sustainable: a) Environmental sustainability.** Buspooling services are frequently operated by the local transit provider as an adjunct to traditional public bus service, the first target of which is to improve the environment sustainability of urban traffic system. **b) Operating sustainability.** Buspooling can only meet a small part of residents' travel demand, and the public property involved is limited. Without additional financial subsidies, the operating agency will need to pursue a certain amount of operating profit. This point should be considered in the operational objective.

Based on the online buspooling platform and the above service principles, in general, an on-demand buspooling trip assumed to form and be executed as follows. First, passengers upload their itinerary information to the mobility platform in advance. Second, the online system matches passengers and vehicles based on a certain matching mechanism under a preset optimization objective. The matching information, including bus schedules, stop locations and the associated candidate groups, is then sent back to both the passengers and the bus drivers. Third, the matched passengers make their trips in the assigned bus. After getting off the bus, lastly, the passengers pay a fare based on the platform's pricing rule and then continue on their respective journeys to their final destinations.

The methodology framework of this paper is as follows, the key to which is the establishment of the matching model and solution algorithm. First, two type of taxi (cruising taxi and ride-hailing) trip data and related operating parameters are introduced as inputs, based on a grid-based time-space network. Second, we formulate the bipartite graph matching problem as a MILP model considering the benefits of vehicle travel distance savings and the buspooling operational revenue. Facing large-scale travel demand in practice, then we built an efficient solution approach balancing computing time and accuracy. 1) Determining the shareable taxi trip set based on a given search cell to reduce the initial decision space. 2) Under the dual constraints of generalized trip cost for passengers and buspooling profit for operators, we establish the feasible trip set. 3) To further utilize the vehicle resources, a method is proposed to merge together similar bus lines. 4) we design a heuristic algorithm based on the scale of feasible passenger groups to resolve this model efficiently. Lastly, we quantify the buspooling potential benefits from multiple perspectives and discuss the improvement strategies in the case study.

For ease of reference, the notation used for the model parameters and variables throughout this paper is listed in **Table 3**.

3.2. Problem formulation

With the help of mobility platform, we seek to formulate the optimal target of the proposed buspooling system and provide useful insights for practice from these solutions. In pursuit of the sustainable development and operation of buspooling access to subway network, it is essential not only to achieve environment benefits but also to ensure a certain profit margin. Therefore, this paper aims to maximize the overall revenue, comprising two aspects: the benefits of saving vehicle travel distance and the operational revenue of the buspooling services. Based on the feasible trip set, the following integer programming equation is formulated:

$$\max \varphi \sum_{(p,b)\in A} \Delta c_{(p,b)} x_{(p,b)} + (1-\varphi)\left(\sum_b \left(\beta_b D_b \sum_p x_{(p,b)} - N_u \cdot \beta_b D_b\right)\right) \tag{1}$$

s.t.

$$\sum_b x_{(p,b)} \leq 1, \quad \forall p \in P \tag{2}$$

Table 3
Notation for indices and parameters.

w, t, r, b	Travel modes of walking, taxi, ride-hailing, buspooling
o_i, d_i	The origin and destination of passenger i
t_o, t_d, t_o', t_d'	Planned departure time, planned arrival time, actual departure time, actual arrival time of passengers
$\alpha, \rho, \gamma, \eta, \zeta$	Unit cost penalties for passengers of in-vehicle travel time by car, in-vehicle travel time by bus, walking time, and departure and arrival schedule deviation
$st_s, st_e, bt_{dep}, bt_{arr}$	Starting station, ending station, departure time, arrival time of buspooling route
T_t, T_b, T_w, T_d	Travel time in taxi trip; travel time in buspooling trip; walking time; deviation time from the schedule
U_w, U_s	Upper threshold of walking time and upper threshold of the time-based scope of the search neighborhood
$x_{(p,b)}$	A 0–1 decision variable; if buspooling trip (p,b) is formed, $x_{(p,b)}=1$; otherwise, $x_{(p,b)}=0$
A, P, B	The set of feasible buspooling trips; the passenger set in the feasible buspooling trip set; the bus set in the feasible buspooling trip set

$$x_{(p,b)} = \{0,1\}, \qquad \forall (p,b) \in A \tag{3}$$

$$\sum_{(p,b)\in A} \Delta c_{p,b} = \sum_{p\in P}\left(\sum_{b\in B}\kappa_{t/r}D_{t/r}(o,d) - \kappa_b D_b(st_s, st_e)\right) \tag{4}$$

Eq. (1) is the objective function and φ denotes a weight coefficient ranging between 0 and 1. The first term of the objective function is vehicle travel distance saving $\Delta c_{(p,b)}$, calculated as the difference between the monetary value of the taxi travel distance and bus travel distance, as shown in eq. (4), where κ_t and κ_b are the monetary value conversion factors for taxi trips and bus trips. $D_{t/r}(o,d)$ and $D_b(st_s, st_e)$ is the travel distance of taxi trip and buspooling trip. The second term is the operational revenue of the buspooling services, equaling the difference between the fare revenue and the operating cost, where β_b is the bus fare per kilometer. The operating cost is estimated based on the fare revenue of a certain number of passengers N_u that can cover the operating cost based on local conditions. Eqs. (2) and (3) provide the constraint conditions. The former guarantees that each passenger is matched with just one bus; the latter is the definitional constraint for the buspooling trip-matching decision variables.

3.3. Solution approach

3.3.1. Feasible trip set clustering method

To guarantee efficiency in addressing the large-scale matching problem, we extract the feasible trips for buspooling from the taxi trip dataset based on a spatial-temporal pruning strategy and passenger-bus interaction matching process. The spatial-temporal pruning strategy is conducted using spatial-temporal similarity constraints for the taxi trips to be shared, while the interaction matching process helps us further determine candidate passengers and the associated bus operating information, under the impact of various matching constraints.

(1) **Spatial-temporal pruning strategy**

Temporal similarity: if the departure time difference between passengers i and j is less than a preset threshold U_t, then these two passengers have temporal trip similarity, shown by the following inequality:

$$|t_{o,i} - t_{o,j}| \leq U_t \tag{5}$$

Search neighborhood: for any grid in the study area, all grids adjacent to it form this grid's search neighborhood S and this grid is regarded as the search cell. Define T_s^O and T_s^D as the time-based scope of the origin search neighborhood S_O and the destination search neighborhood S_D for one particular search cell, respectively. Let the ceiling of the time-based scope of the search neighborhood be U_s, such that $T_s^O \leq U_s, T_s^D \leq U_s$, as shown in Fig. 2.

Spatial similarity: if a group of passengers shares both origin search neighborhood S_O and destination search neighborhood S_D, then these passengers have spatial similarity.

Spatial-temporal similarity: if a group of taxi trips has both temporal similarity and spatial similarity, then they have spatial-temporal similarity and meet the initial requirement for forming a buspooling trip.

(2) **Other constraints for feasible trips**

Tolerable walking time: the walking time from passengers' origins to the starting bus stations T_w^O or from the terminal stations to the passengers' destinations T_w^D should not be too long. Let the upper limit of the tolerable walking time be U_w, so that $T_w^O \leq U_w, T_w^D \leq U_w$, as shown in the timeline of Fig. 2.

Minimum passenger capacity: considering the need for a minimum operating profit, it is necessary to preset the minimum passenger capacity for a buspooling trip, which is denoted by N_b.

Initial feasible trip set: under the constraints of spatial-temporal similarity and the tolerable walking time ceiling, if the size of a passenger group within the temporal-spatial network is beyond the minimum passenger capacity of a buspooling vehicle, i.e. $N(S_O, U_t, S_D) \geq N_b$, as shown in Fig. 2, then we define these taxi trips as one element of the initial feasible trip set for forming buspooling trips, and all such elements form the initial feasible trip set.

Travel cost saving constraint: according to the cost-effective principle, passengers should make some kind of saving when shifting from taxis to buspooling, namely the generalized travel cost of a buspooling trip should be less than the cost of the original taxi trip.

The generalized travel cost includes the service fare and various travel time values. The taxi trip cost includes the in-vehicle time value and the service fee, as shown in eq. (6), where the capital letters C, T, F denote the generalized travel cost, travel time and trip fare, α denotes the unit cost factor of the in-vehicle travel time, and the subscripts t, r denote the travel modes of cruising taxi and ride-hailing.

$$C_t(o_i, d_i) = \alpha_t T_t(o_i, d_i) + F_t(o_i, d_i); C_r(o_i, d_i) = \alpha_r T_r(o_i, d_i) + F_r(o_i, d_i) \tag{6}$$

When taxi passenger i shifts to using integrated transit services, in general, the generalized cost of a buspooling trip $C_b(o_i, d_i)$ consists of four components: (1) the fare of the buspooling trip based on the travel distance, (2) the effort penalty cost due to the additional walking from the origin to the starting stop and from the ending stop to the destination, (3) the in-vehicle travel time cost, and (4) the schedule deviation penalty, including the requirement to leave home and/or reach the destination early or late. Then, we can give the generalized buspooling trip cost as in eq. (7). $D_b(st_s, st_e)$ and $T_b(st_s, st_e)$ are the travel distance and travel time of this buspooling trip; $T_w(o_i, st_s)$ and $T_w(d_i, st_e)$ are the origin walking time and destination walking time; $C_{td}(o_i, d_i)$ is the schedule deviation time, including the origin schedule deviation ΔT_{o_i} and the destination deviation ΔT_{d_i}, as shown in eq. (8); μ is the trip fare factor per kilometer and $\gamma, \rho, \eta, \zeta$ are the unit cost factors of the associated time values, which can be estimated using real data or by referring to

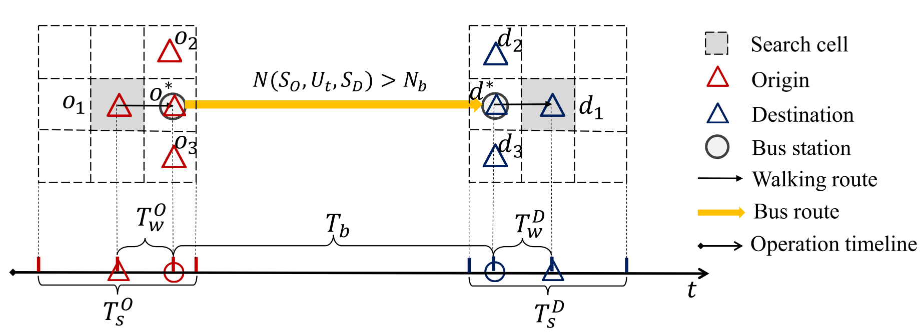


Fig. 2. The forming of a buspooling trip based on the search neighborhood in a temporal-spatial network. Note that the candidate bus stops are based on the locations of each passenger's origin or destination point in this search neighborhood, denoted by (o^*, d^*).

previous academic literature.

$$C_b(o_i, d_i) = \mu D_b(st_s, st_e) + \gamma(T_w(o_i, st_s) + T_w(d_i, st_e)) + \rho T_b(st_s, st_e) + C_{td}(o_i, d_i) \tag{7}$$

$$C_{td}(o_i, d_i) = \eta \Delta T_{o_i} + \zeta \Delta T_{d_i} \tag{8}$$

For the schedule deviation time due to shifting from taxis to buspooling, it is assumed that the passengers will depart earlier or later to match the buses' operating schedule. Hence the origin schedule deviation time is the difference between the planned departure time of the passenger in the original taxi trip and the actual departure time of the passenger so as to arrive at the bus station on time, where t_{oi} and t'_{oi} are the planned start time and actual start time of a passenger, as shown in eq. (9). The destination schedule deviation is the difference between the passenger's planned time of arriving at their workplace when traveling by taxi and the actual time of arrival when using buspooling, where t_{di} and t'_{di} are the planned and actual arrival times of the passenger, as shown in eq. (10). Considering the distinction between the late and early penalties at the origin and destination (Long et al., 2018; Liu & Liu, 2020), we take $\eta^+(\zeta^+)$ and $\eta^-(\zeta^-)$ as the penalty factors for leaving (arriving) earlier or later than they would have planned when using taxi trips, respectively.

$$\eta \Delta T_{oi} = \eta^+ \max\{(t_{oi} - t'_{oi}), 0\} + \eta^- \max\{(t'_{oi} - t_{oi}), 0\} \tag{9}$$

$$\zeta \Delta T_{di} = \zeta^+ \max\{(t_{di} - t'_{di}), 0\} + \zeta^- \max\{(t'_{di} - t_{di}), 0\} \tag{10}$$

If a group of passengers in the initial feasible trip set make travel cost savings due to shifting from taxis to buspooling, as shown in the following eq. (11), then we define this passenger group as one element of the feasible trip set, with all such elements forming the feasible trip set. N is the number of passengers in a buspooling trip; $C_b(o_i, d_i)$ is the generalized buspooling trip cost for passenger i and $C_{t/r}(o_i, d_i)$ is the cruising taxi or ride-hailing trip cost for passenger i.

$$\sum_{i=1}^{N} C_b(o_i, d_i) > \sum_{i=1}^{N} C_{t/r}(o_i, d_i) \tag{11}$$

$$N(\Delta C) = \sum_{i=1}^{N} C_b(o_i, d_i) - \sum_{i=1}^{N} C_{t/r}(o_i, d_i) \tag{12}$$

(3) **Identifying feasible trip groups based on the interaction process**

According to the above constraints and definitions, the matching process is conducted as follows: (1) extract the high-frequency trip groups within preset time-space windows for each search cell, where the size of any trip group should reach the minimum passenger capacity (MinPC) threshold, i.e. $N(S_O, U_t, S_D) \geq N_b$. (2) Establish the candidate station set based on the actual pick-up or drop-off points of the taxi trips and estimate the walking time of passengers in the associated search neighborhood. If a passenger P_k could not reach a given bus station on foot within the required limit, i.e. $T_w > U_w$, remove this passenger for that candidate station, and then remove any unsatisfied bus stations according to the constraint MinPC. If the candidate station meets the constraints, continue; otherwise, return to step 1. (3) Build the candidate bus departure time set based on the latest arrival time of the taxi passengers and compare the buspooling schedule with the original taxi trip schedule. (4) Estimate the generalized travel cost based on eqs. (6) to (12) for each high-frequency trip group and remove any trip groups without cost savings, i.e. $N(\Delta C) \leq 0$ (see eq. (12)). If the remaining trip group meets the constraint MinPC, continue; otherwise, return to step 2. (5) Bring the remaining feasible trip groups, bus stations and bus departure times into the matching model, as shown in the flow chart in Fig. 3.

Through this passenger-bus interaction matching process, we can obtain the feasible trip set $A\{(B, P)\}$, including the buspooling vehicles and the associated passengers. The candidate bus set is defined as $B\{b(st_s, st_e, t_{dep}, t_{arr}) | \forall b \in A\}$, including the location information of the starting and terminal stations, and the schedule information. The candidate passenger set is defined as $P\{p(o_i, d_i, t'_{o_i}, t'_{d_i}) | \forall p \in A\}$, including the location information of the passengers' origin and destination points and the schedule information for the buspooling trips. The operating information is selected from the taxi passengers' real itinerary information, and is finally determined using the system matching objective. This matching mechanism can help remove infeasibly matched groups of candidate passengers and buses. In other words, it determines whether a buspooling trip can be made, where the bus stations are located and when the buses should plan to depart, based on the specific demands of the candidate passengers.

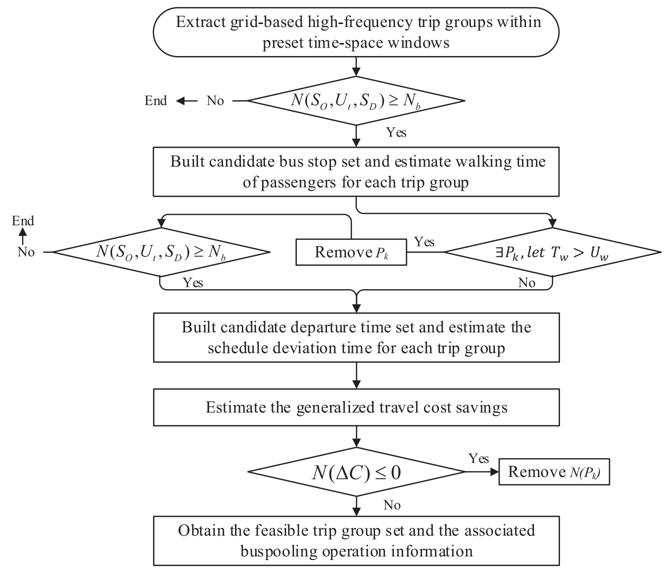


Fig. 3. Flowchart of identifying the feasible trip groups based on the interaction process.

3.3.2. Similar line merging method

To further improve the utilization of vehicle resources, it is worth merging buspooling lines with spatial-temporal similarity (STS) in the feasible trip set. Considering the car-user-oriented service principles of buspooling, we should try to provide a quasi-car mobility service and reduce any additional costs due to stops. Hence, here we design a combined method for double-similar-line, as shown in the flowchart in Fig. 4, with the specific steps as follows:

(1) **Estimate the potential cost savings of line combination**

For any element A_i in the feasible trip set, we can regard it as one potential bus line with matched vehicle and passenger information. For passengers on any two bus lines A_i and A_j ($i \neq j$), we can obtain their travel cost savings from switching from taxis to buspooling based on the estimation of the generalized travel cost proposed in Section 3.3.1, which can be denoted by $CS_0^{A_i}$ and $CS_0^{A_j}$. On the other hand, additional pick-ups and drop-offs due to combining the two lines will cause time delays and reduced comfort, and the total loss due to additional stops should have a positive correlation with both the number of loading passengers and the dwell time. Here, we define the minimum loss due to additional stops ϑ as in eq. (13), where N_b is the MinPC, τ is the stop dwell time and χ is the comfort penalty factor. If the sum of the travel cost savings is greater than the additional loss due to combining the lines, namely $CS_0^{A_i} + CS_0^{A_j} \geq \vartheta$, then we further evaluate the spatial-

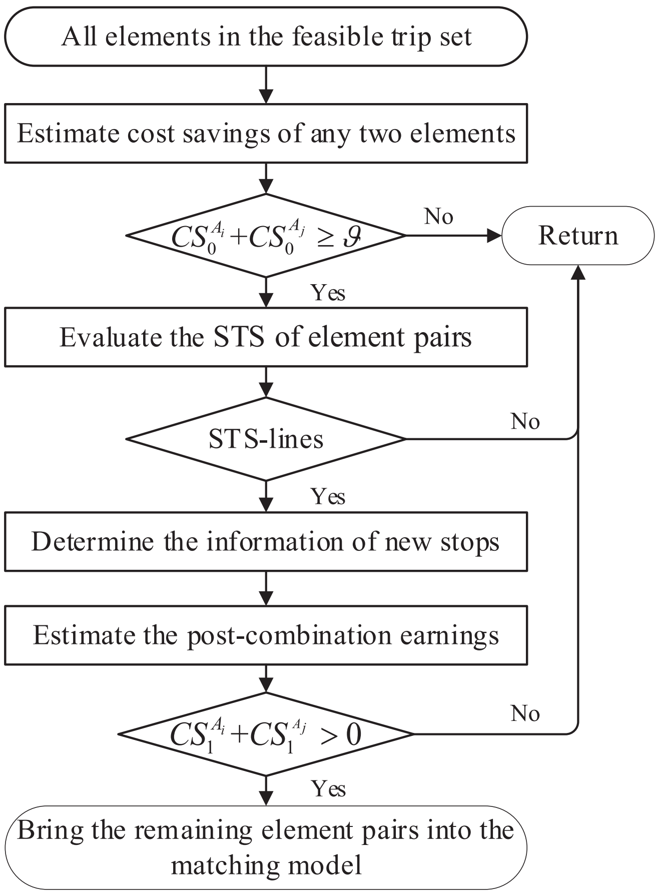


Fig. 4. Flowchart for merging buspooling lines with spatial-temporal similarity.

temporal similarity of these two bus lines; otherwise, we return to the first step.

$$\vartheta = 2N_b \times \chi\tau \tag{13}$$

(2) **Evaluate the spatial-temporal similarity of the bus lines**

If the spatial-temporal relationship between lines A_i and A_j meets the following three conditions, we define these two lines as STS-lines: (1) spatial similarity: the travel distance between the origins (destinations) of lines A_i and A_j, denoted by O_iO_j (D_iD_j), is less than 5 km; (2) route similarity: the detour distance due to additional pick-ups and drop-offs must be restricted, thus the route deviation distance, denoted by the sum of O_iO_j and D_iD_j, must be less than the sum of the original buspooling route distances, O_iD_i and O_jD_j; (3) temporal similarity: there is overlapping in the operational hours of the two lines. If these conditions are met, these STS lines go on to the next step.

(3) **Determine the intermediate station information**

Based on the station locations of the two STS lines, we can determine the shortest routes and associated intermediate stops of the combined line. The departure times of the intermediate stations are calculated based on the departure time from the originating station and the distance along the route, while the positioning of the intermediate stations follows the interaction process used earlier for the passenger choice and bus operations, achieved through the following optimization model based on the actual boarding and alighting points of the passengers.

(4) **Estimate the cost savings from combining the lines**

According to the updated schedule and route information, we need to calculate the generalized travel cost for the passengers on each merging line. If the involved passengers' travel cost savings are positive, namely $CS_1^{A_i} + CS_1^{A_j} > 0$, we consider that these two direct lines can be combined and test the influence of their combination on the matching performance. Otherwise, we return to the first step.

3.3.3. k-HPCG heuristic solution algorithm

When identifying the feasible trip groups for buspooling, we preset the MinPC N_b. Let N_c denote the maximum bus capacity, hence, the possible number of passengers in a buspooling trip N is from N_b to N_c. The theatrical number of candidate passenger groups in each buspooling trip can reach $\sum_{m=N_b}^{N}\sum_{n=N_b}^{N} C(m,n)$, $m \geq n$, $N_b \leq N \leq N_c$, where the $C(m,n)$ is the number of combinations of m elements taken from n distinct elements. Such a large-scale matching problem would pose a huge challenge for a mobility platform with limited computing power. The process of finding the optimal solution, while considering all feasible passenger groups and meeting on-demand service standards, could be complex and time-consuming. Considering a combination including more passengers may lead to a better matching performance, therefore, a heuristic algorithm based on the k-Highest Passenger Capacity Group (k-HPCG) is proposed. Depending on the value of k, this algorithm considers the feasible passenger groups with the highest (k = 0), second-highest (k = 1), and k-highest passenger occupancies within the time-space network, and the theatrical number of candidate passenger groups can be reduced to $\sum_{m=N-k}^{N}\sum_{n=N-k}^{N} C(m,n)$, $0 \leq k \leq N - N_b$. A smaller k means less feasible passenger groups and less computation time. By taking into account the computational time and the solution gap, the value of k is determined, which in turn determines the optimal passenger group size that best suits the case scenario. The specific steps of the k-HPCG heuristic algorithm are as follows:

1) Defining and computing the error level of the matching model. Under some maximum acceptable computational time, we can seek to obtain the maximum system benefit $B_{\max}$ with the highest value of k. For decreasing k, we can calculate the associated system benefit B_k and the solution error. The error level e_k is shown in eq. (14), and is between 0 and 1.
2) Defining and computing an evaluation index for solution efficiency. Under varying values of k, we can record multiple groups of computational times and error levels when solving the model. After the normalization processing, the updated computational time $\bar{t}_k$ and error level $\bar{e}_k$ are used to quantify the solution efficiency, as shown in eq. (15), where λ denotes the weight coefficient and ranges between 0 and 1. This index can help buspooling platform operators choose the most appropriate solution scheme in practice.

$$e_k = \frac{B_{\max} - B_k}{B_{\max}} \tag{14}$$

$$E_k = \frac{1}{\lambda\bar{t}_k + (1-\lambda)\bar{e}_k} \tag{15}$$

3.3.4. Performance evaluation indexes

To evaluate the potential benefits of buspooling under various scenarios, we define four ratio indexes from different perspectives, which are shown below: index (16) is the buspooling matched number (MR), index (17) is the passenger cost savings (CR), index (18) shows the vehicle travel distance reduction (DS) and index (19) gives the operating profit (OP) of the buspooling, where the asterisk indicates the matched buspooling passengers in the solution of the optimization model.

$$MR = \frac{\sum_{(p,b)\in A} x^*_{(p,b)}}{|P|} \times 100\% \tag{16}$$

$$CR = \frac{\sum_{(p,b)\in A} \Delta C_p x^*_{(p,b)}}{\sum_{p=1}^{|P|} C_p} \times 100\% \tag{17}$$

$$DS = \sum_{p\in P} \left(\sum_{b\in B} \kappa_{t/r} D_{t/r}(o,d) - \kappa_b D_b(st_s, st_e) \right) x^*_{(p,b)} \tag{18}$$

$$OP = \sum_{b} \left(\beta_b D_b \sum_{p} x^*_{(p,b)} - N_u \beta_b D_b \right) \tag{19}$$

3.4. Application to the case of Beijing

Taking Beijing, China as a case study, we collected trip data for both cruising taxis and online car-hailing within the same period, as a proxy of car-use travel demand. More specifically, we revealed a co-opetition relationship between taxis and subway, and took the passengers who used subways and taxis cooperatively as potential users of the bus-pooling access to subway. These users were then input into the matching model to obtain the optimal solution and quantify its societal benefits. The model and algorithm parameters will now be explained in detail before the application to the case.

3.4.1. Dataset and preliminary analysis

According to statistics, the permanent population of Beijing reached 21.729 million in 2016, with over 75 % of the population living and working in the urban center, within the 6th Ring Road (Liao et al., 2020). To alleviate road congestion and air pollution in the city, the number of subway lines has continuously been increased. As of March 2016, Beijing had completed the construction of 18 subway lines, with a total of 278 subway stations. The majority of the stations and lines are located within the 6th Ring Road. This study focuses on that area, as shown in Fig. 5.

The cruising taxi data used in this study consists of taxi GPS trajectory data, collected from March 7th, 2016 to March 13th, 2016. The car-hailing taxi consists of online order data for the DiDi Express services, sourced from the "DiDi Chuxing" mobile transportation platform in China. The time period of that order data aligns with the time period of the regular taxi data. In the original dataset, the fields relevant to this study include vehicle code, order code, passenger pick-up and drop-off locations, passenger pick-up and drop-off times, travel distance, and service fare. After data pre-processing, the dataset contains 5.38 million regular taxi trips and 4.42 million car-hailing trips over one week.

According to previous research (Jiang et al., 2018; Wang & Ross, 2019), taxi trips that can be completely replaced by the subway are categorized as competitive with the subway, while taxi trips which one end is within the subway's service range and the other end is outside of it are classified as cooperative with the subway. Based on the spatial-temporal relationship between taxi trips and the subway network, we define and extract two types of taxi trips as follows.

Subway-competing taxi trips (SCTTs): the departure time is within the operating hours of subway routes and the origin and destination of this taxi trip are both within walking distance of subway stations. The associated taxi passengers are defined as competitive passengers.

Subway-extending taxi trips (SETTs): the departure time is within the operating hours of subway routes and the origin (or destination) of this taxi trip is within walking distance of a subway station, while the destination (or origin) is not. The associated taxi passengers are defined as cooperative passengers.

Mapped station: Given a spatial location, the nearest subway station to that location is referred to as that location's mapped subway station.

Considering the higher vehicle capacity and demand for integrated transit trips, buspooling services are mainly launched for long-distance commuters in the initial stages. Hence, the target group selected for the buspooling system discussed in this paper are SETTs during rush hours in the Beijing metropolitan area.

3.4.2. Model and solution algorithm parameters

(1) **Model parameters in basic scenario**

Search neighborhood and spatiotemporal similarity: According to the "Big Data Analysis Report on Public Transport in Major Chinese Cities in 2017" by Amap, a popular Chinese digital mapping service, the average walking distance to access public transit services is about 0.93 km in Beijing. We take 100 m/min as the walking speed of commuters (Galiza et al., 2011), and then the tolerable walking time is about 10 min. When searching for feasible trip groups, the side length of the spatial grid size is set to 1 km, just covering the walking distance threshold. Considering commuters are more sensitive to travel time, we set a smaller time span, 10 min, as the threshold of temporal trip similarity, and considering the passenger flow on and off the bus is higher during rushing hours, the dwell time of an intermediate stop for merging buspooling lines cannot be neglected and is taken as 1 min.

Buspooling fare and passenger capacity: The fare for buspooling, β_b, is designed by two criteria. First, we implement rule-based pricing using a cost calculation function of distance travelled, which is a widely accepted fair pricing method. Second, considering the limited public property and profit requirements, the pricing level of buspooling

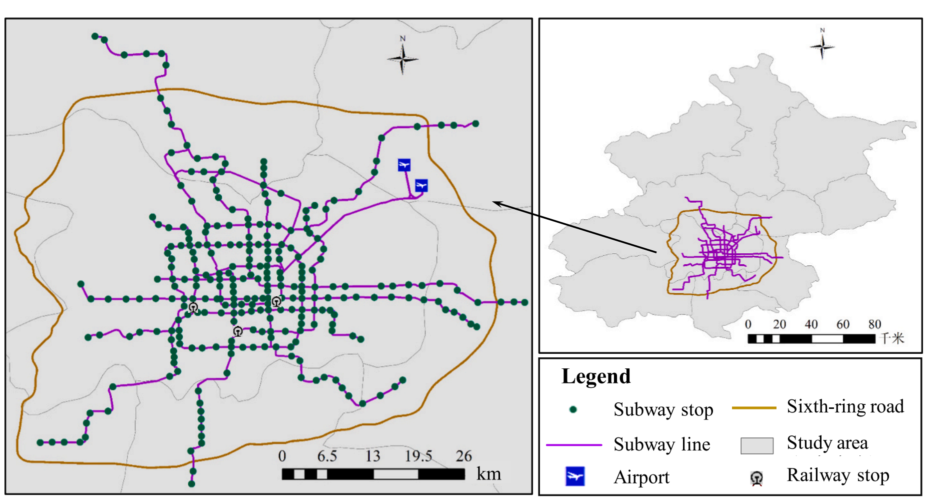


Fig. 5. Study area and its subway network.

services should be higher than conventional bus services and lower than private taxi, which is at 0.4 RMB/km and 1.9 RMB/km on average in Beijing, respectively (BTI, 2017). Here we determine the buspooling fare at 1 RMB/km. For passengers on buspooling lines with intermediate stops, a discounted fare of 0.75 RMB per kilometer is offered to offset the additional stop for participants. Additionally, in the basic scenario, the minimum passenger capacity for the buses is set at 4 people, which is not less than the maximum number of passengers allowed in a taxi. This is done to differentiate between buses and cars in terms of passenger capacity. The regulated passenger capacity for a buspooling vehicle is 12 people.

Travel time value: The generalized cost calculation for the taxi and buspooling trips involves multiple parameters regarding travel time value. Based on some relevant prior work (Abrantes & Wardman, 2011; Douglas & Jones, 2013; Liao et al., 2020; Wardman et al., 2016), these parameters for the basic scenario of this case are summarized in the **Table 4**.

(2) **k values for heuristic solution algorithm**

Considering that higher k values make solving the model more difficult, here we use a small proportion of the sampled data to explore the potential relationship between the value of k and changes in the model efficiency, helping us to select of k values for larger proportions or the entire dataset. In this case, 30 %, 40 % and 50 % of the sampled data is used to solve the buspooling matching model under different passenger group sizes and k values. To ensure the feasibility of the on-demand matching system for practical applications, the maximum acceptable computational time for the model, based on a desktop computer with a standard configuration, is set to 2 h. The weight coefficients are set to 0.5 and the maximum value of k is set to 5. Then, we calculate the solution error and efficiency of the k-HPCG heuristic algorithm based on formulas (14) and (15). The results are shown in Table 5.

It can be observed that, given the sampled proportion of taxi passengers, as the passenger group scale expands, the computational time of the model increases rapidly, while the model's solution error decreases significantly. Regarding the efficiency metric of the matching model, it shows an increasing-then-decreasing trend as the passenger group size expands. As the sampled proportion increases, the k value with optimal solving efficiency declines from $k = 3$ to $k = 2$. In larger-scale data scenarios, it can be inferred that the k value should be less than 3. However, if the objective is to achieve the optimal solution or the computing power is sufficient, a larger passenger group size should be considered.

In this paper, all computational experiments were conducted on a desktop computer configured with an Intel ® Core™ i7–4790 processor and 16GB of RAM. The model was built using the C# programming language, and Cplex was used to implement the optimization model for the buspooling matching and solving. In the basic scenario, where the passenger participation rate was set at 70 % and $k = 2$, the model's solving time was 8 min. However, when considering the merging of similar lines, the solving time increased to 26 min.

Table 4
Model parameter values.

Parameter	Value	Parameter	Value
α	1.03 ¥/min	η^+	0.34 ¥/min
ρ	1.13 ¥/min	η^-	0.44 ¥/min
γ	1.75 ¥/min	ζ^+	0.95 ¥/min
N_b, N_u	4, 7 persons	ζ^-	3.01 ¥/min
β_b	1¥/km	χ	2.86 ¥/min

4. Results and discussion

4.1. The travel patterns of taxi passengers

Upon classifying all of the taxi passengers in the designated scenario, it was discovered that competitive passengers, on average, constitute 49.0 % of the total, while cooperative passengers account for an average of 39.5 %. More specifically, when it comes to cruising taxis, competitive passengers make up approximately 58.8 % of the total, whereas cooperative passengers comprise around 32.9 %. For ride-hailing services, competitive passengers represent around 39.0 % of their user base, while cooperative passengers account for approximately 46.1 %. Overall, taxis and the subway primarily have a competitive relationship, with a secondary cooperative aspect. Upon further examination, cruising taxis predominantly compete with the subway, whereas ride-hailing services exhibit a more noticeable cooperative relationship with the subway. Further analysis of competitive and cooperative passengers' travel characteristics from the spatio-temporal perspective yields the following results.

Fig. 6 shows the variation in the proportions of competitive and cooperative taxi passengers in the total passenger flow for both traditional taxis and ride-hailing services, across different hours of the day. According to Fig. 6(a), for traditional cruising taxis, the temporal distributions of the competitive and cooperative passengers exhibit contrasting trends. Overall, the fluctuations are minimal, with the number of competitive passengers consistently higher than that of cooperative passengers. In Fig. 6(b), the temporal distributions of competitive and cooperative passengers in ride-hailing services also display contrasting trends, but with more pronounced fluctuations compared to those for the traditional taxis. Cooperative ride-hailing passengers show a distinct peak during the morning rush hour, followed by a relatively stable pattern, indicating that for commuters there is a strong connection with subway services.

Figs. 7 and 8 present the spatial distribution heatmaps of competitive and cooperative passengers' origins on a typical workday. In Fig. 7(a), it is observed that, for traditional taxis' competitive passengers, the origins are primarily concentrated in the city center, forming two hotspot areas: the financial district, with areas like the Financial Street and the China World Trade Center, and the urban transportation hub area. In Fig. 7(b), the competitive ride-hailing passengers mainly originate from commercial and office areas, with no distinct hotspots near high-speed railway stations or airports. This could be attributed to strict control measures imposed by local authorities regarding ride-hailing services near transportation hubs.

In Fig. 8(a), the heatmap shows that the origins of cooperative traditional taxi passengers are more spatially dispersed. Compared to competitive passengers, their hotspots extend towards the outskirts of the city, with concentrations near terminal subway stations. In Fig. 8(b), the origins of cooperative ride-hailing passengers spatially expand further outwards, with an increased proportion in suburban areas such as Changping, Shunyi, Tongzhou and Daxing. The spatial distributions of the competitive and cooperative passengers reveal that the travel areas of competitive passengers are concentrated in the city center, while cooperative passengers' travel areas extend towards the outskirts of the city, with a diverse range of hotspots. In particular, ride-hailing services play a role in facilitating access to public transportation for residents in suburban areas.

4.2. Potential benefits of buspooling system

Taking SETTs during the morning rush hour on a typical workday as the target group, we solved the matching model for the busppoling system, using the k-HPCG heuristic algorithm with $k = 2$ and a 1:1 ratio for the objective function's weights. The analysis of the matching performance can be approached from three aspects: the basic scenario, a visualization analysis of the bus lines, and buspooling access to different

Table 5
Solving efficiency of the algorithm under different k values.

Sampled proportion		Feasible passenger group sizes					
		k = 0	k = 1	k = 2	k = 3	k = 4	k = 5
	Computational time (min)	0.1	0.2	0.3	0.4	0.8	4.0
30 %	**Solution error**	47.3 %	27.4 %	15.8 %	8.3 %	5.1 %	0.0 %
	Solving efficiency	2	3.3	5.16	**7.92**	6.92	2
	Computational time (min)	0.2	0.4	1.0	3.0	12.0	56.0
40 %	**Solution error**	59.6 %	37.1 %	19.4 %	12.4 %	7.3 %	0.0 %
	Solving efficiency	2	3.16	5.64	**7.24**	6.16	2
	Computational time (min)	0.5	1.0	3.0	13.0	93.0	>120.0
50 %	**Solution error**	49.5 %	31.0 %	13.0 %	4.8 %	0.0 %	/
	Solving efficiency	2	3.16	**6.9**	6.48	2	/

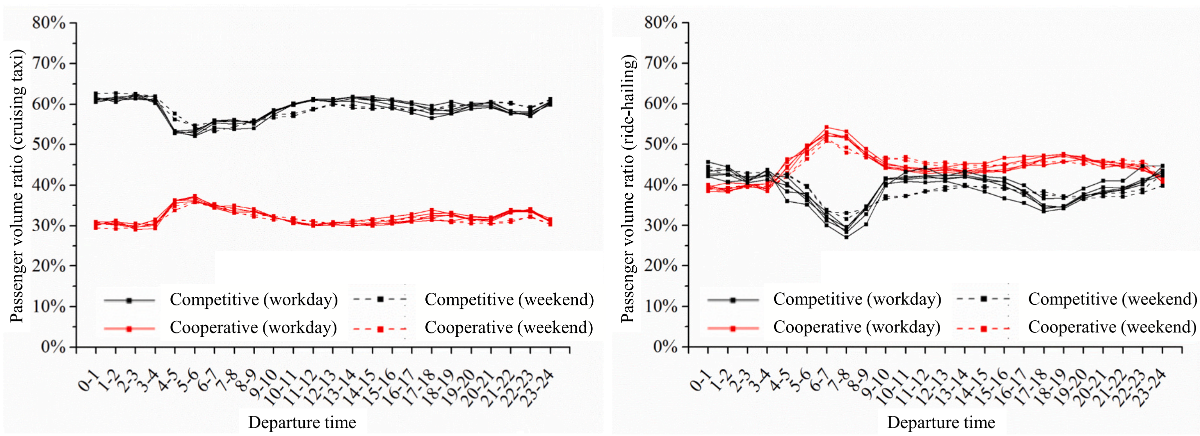


Fig. 6. Temporal distribution of the proportions of SCTTs (a) and SETTs (b).

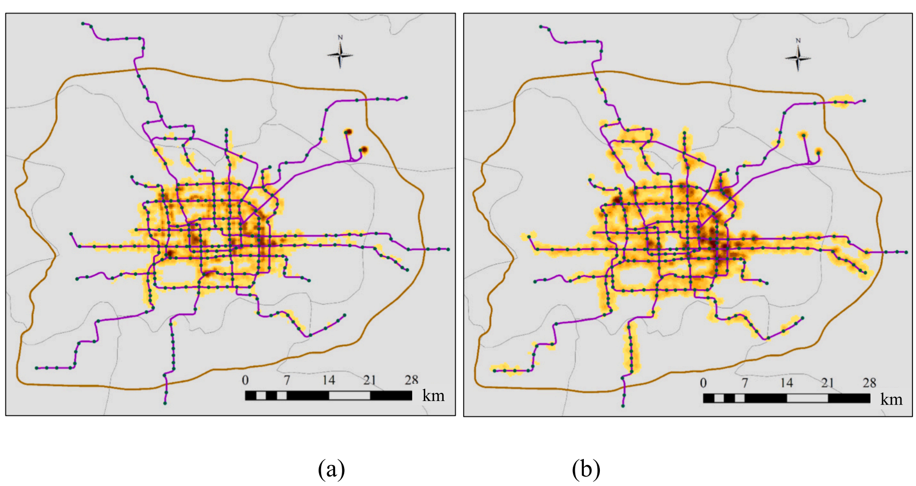


Fig. 7. Trip origin spatial distribution of (a) competitive cruising taxi passengers and (b) competitive ride-hailing passengers on a workday.

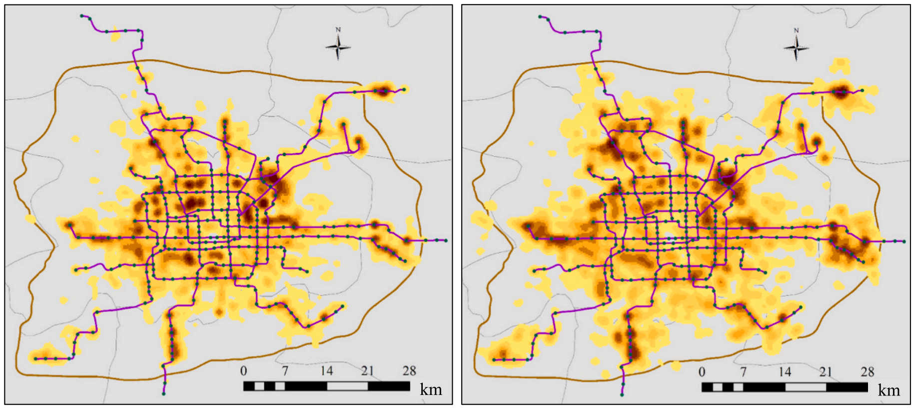
types of subway stations.

4.2.1. *Basic matching performance*

In the basic scenario, during the morning rush hour, the final successful matching resulted in 1049 passengers out of a total of 30,176 cooperative taxi passengers, achieving a matching rate of 3.48 %. A total of 188 buspooling routes/lines were generated, with an average passenger occupancy of 5.58 individuals. Among these lines, 63 had a passenger count of 6 or more, indicating a seat occupancy rate higher than 50 %. Due to factors such as route similarity and additional stop costs, only 41 lines were identified as having the potential to be merged, with an average occupancy of 8.93 individuals, illustrating there could be significant advantages in resource utilization.

In terms of cost savings for the buspooling passengers shifting from taxis, the average saving per trip was 21.66 ¥, resulting in an individual saving of 3.88 ¥. The overall cost saving for the system was 6.11 %. The savings were even higher for merging buspooling lines, reaching 36.96 ¥ per trip with an individual saving of 4.41 ¥. In the basic scenario, approximately 62.51 % of users arrived at their destinations earlier than planned, and 73.45 % experienced a delay of no more than 5 min, highlighting the reliability of the buspooling-subway integration in terms of commuting time.

From the perspective of vehicle operating income, buspooling proves to be a profitable transportation mode, generating an operating income



(a) (b)

Fig. 8. Trip origin spatial distribution of (a) cooperative cruising taxi passengers and (b) cooperative ride-hailing passengers on a workday.

of 1421.8 ¥ per morning peak hour. This is significantly different to conventional bus systems that often require substantial subsidies. Notably, merging buspooling lines accounted for only 21.8 % of the lines but contributed nearly 70 % of the operating income. This demonstrates significant economic advantages.

From the perspective of environmental benefits, buspooling represents a sustainable transportation model, significantly reducing vehicle road mileage, and reducing carbon emissions by approximately 2 tons. This reduction represents a total environmental benefit of 5119.2 ¥. The total mileage reduction for passengers on merging buspooling lines provided a benefit of 1840.3 ¥, with an average benefit of 5.03 ¥ per passenger, slightly higher than the average level.

In the case where the merging of similar lines was not considered, the matching rate for buspooling services was 3.37 %, with a system cost savings rate of 6.83 %, a carbon emissions reduction of 1.9 tons, and an operating income of 885.5 ¥. These results demonstrate that, although the effect of merging lines on the number of matched passengers, travel cost savings, and environmental benefits is relatively small, it does play a significant role in improving operating income.

4.2.2. *Visualization analysis of buspooling lines*

In order to depict the spatial characteristics of the buspooling stations and passengers, a visualization analysis of the buspooling lines was

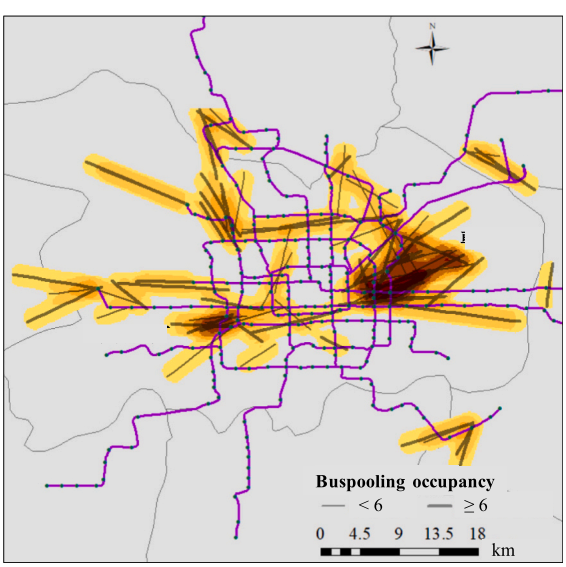


Fig. 9. Spatial distribution of buspooling lines.

conducted as shown in Fig. 9. The black line segments in the figure represent the bus lines, with the width of each line segment indicating the number of shared passengers on the bus. The darkness of the color indicates the density of buspooling lines in a particular area. It can be observed that there are two high-density corridors for buspooling passengers. The common characteristic of these two corridors is that the starting stations are not within the service range of any subway stations, while the endpoints are highly popular with travelers and are also important interchange stations in the subway system. In the suburban areas of the city, there are some buspooling lines that connect to endpoint subway stations, which could effectively extend the service range of the subway and enhance its attractiveness. The consistency between the distribution of cooperative passengers and the buspooling lines indicates that buspooling services can effectively enhance subway accessibility for residents in suburban areas.

Fig. 10 illustrates two typical buspooling lines for which the method of similar line merging is used. The incorporation of intermediate stops enhances the passenger capacity of the bus, albeit at the expense of higher detouring costs and waiting times for the sharing passengers. The directional flow of the passengers on Line 1 signifies that buspooling not only facilitates passengers' commutes to subway stations for transfers but also addresses their travel needs between the subway stations and more distant destinations. Without the buspooling services, passengers on Line 1 would need to transfer multiple times and walk long distances to complete their trips. This highlights the efficiency and convenience buspooling services could provide. Line 2 connects passengers from two neighboring communities, with only one intermediate stop, accommodating a capacity of 11 passengers. Compared to one-stop buspooling service, the merging of similar lines significantly improves vehicle utilization and operating revenue, and offers a lower cost for passengers.

4.2.3. *Matching performance access to different subway stations*

According to the physical topological structure, subway stations can be categorized into transfer stations, terminal stations and regular stations. Based on this classification, the performance of the integration between each of these types of subway stations and buspooling can be analyzed and summarized, as shown in Table 6.

There are 29 buspooling lines connecting with terminal stations, serving 174 passengers, and achieving a matching success rate of 4.9 %. This indicates a higher spatio-temporal similarity among passengers, making it easier for successful ridesharing to be achieved. The utilization rate of buspooling vehicles is higher at terminal stations, and longer average distances are covered per line, resulting in significantly higher average operating profits and mileage savings. However, the larger number of shared passengers on a single line may lead to increased schedule deviation and walking time costs. Consequently, the average

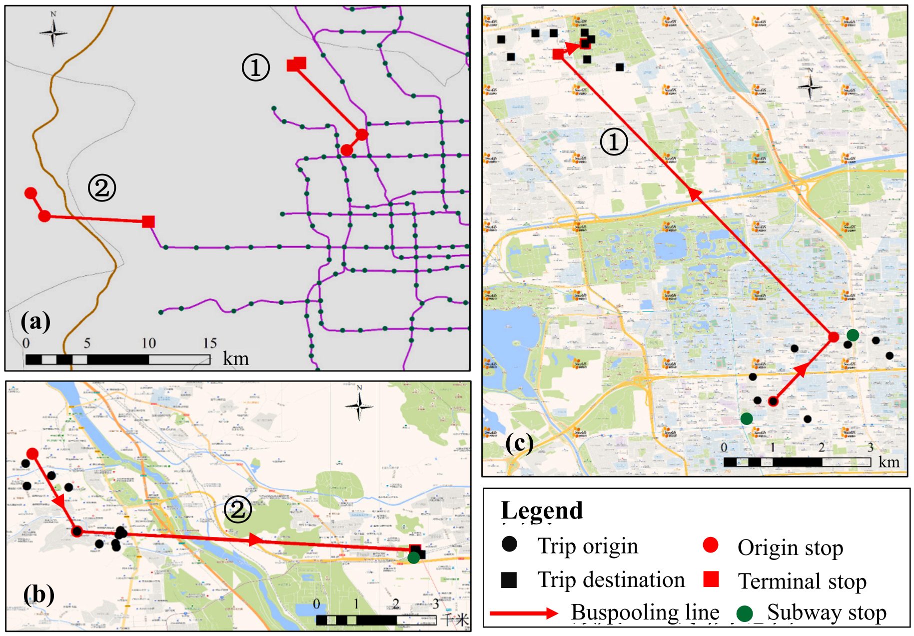


Fig. 10. Similar buspooling line merging results

Table 6
Statistics for the matching results of buspooling passengers connecting to different types of subway stations.

Station type	Number of lines	Average passenger load	Average travel distance (km)	Average operating profit (CNY)	Average mileage savings (CNY)	Average cost savings per passenger (CNY)
Regular stations	142	5.63	9.43	7.76	27.46	4.92
Terminal stations	29	6.00	10.99	10.37	31.31	3.46
Transfer stations	17	4.47	8.57	1.10	18.34	6.54

cost savings for passengers using buspooling at terminal stations are relatively lower.

The buspooling lines connecting with regular subway stations amount to 142, accounting for three-quarters of the total. These routes serve a total of 799 passengers, but the matching success rate is only 3.5 %. The performance of buspooling lines at regular stations is at a moderate level.

Only 17 buspooling lines connect with transfer stations, serving 76 passengers. The matching success rate is only 2.1 %. This suggests that achieving large-scale ridesharing for cooperative taxi passengers at transfer stations will be challenging. The average passenger load per vehicle is less than 5, resulting in lower operational indicators, except for the level of cost savings per passenger.

4.3. *The impact of sharing penalty of passengers with different unit time costs*

In order to enhance the potential benefits of the buspooling system, we conducted a series of sensitivity experiments to analyze the impact of the sharing penalty of passengers, including additional walking time and time deviation due to buspooling, on the matching performance under different unit time costs. We set the travel time cost coefficient to 0.5, 1, 1.5, 2 and 2.5 times that of the baseline scenario. Furthermore, we adjusted the walking time (WT) penalty coefficient and the schedule deviation time (SDT) penalty coefficient to 0.5, 1.0, and 1.5 times the baseline scenario. We then collected data on the matching success rate, passenger cost savings, carbon emissions reductions, and total revenue levels of the buspooling system. It is worth noting that all sensitivity experiments were conducted without considering similar-line merging scenarios.

The results of the sensitivity analysis reveal that, under the given penalty coefficients, the matching success rate of the buspooling exhibits a sharp decline as the time cost coefficient increases. This can be seen in Fig. 11. This decline may be attributed to the additional time costs associated with the buspooling compared to taxi trips (such as walking time, transfer time and SDT costs), making the impact of the time cost coefficient more significant in the intermodal system. On the other hand, under the given time cost, increasing the penalty coefficient also leads to a noticeable decrease in the system's matching success rate. In particular, the variation in the penalty coefficient for the SDT has a more significant impact. This could be attributed to the fact that SDT includes factors such as arriving early, arriving late, leaving early and leaving late, which have a greater influence on the estimated travel cost than the

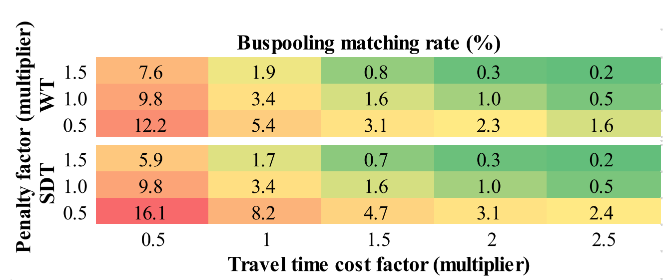


Fig. 11. Relation between travel time cost factor, penalty factor of buspooling passengers and matching rate.

penalty for walking time.

Considering both coefficients, the highest system matching efficiency, reaching 16.1 %, is achieved when both coefficients are set to half the baseline scenario values. Therefore, passengers with lower wages and those who are less sensitive to additional sharing penalty are likely to be the primary users. When the penalty coefficient is larger, the negative impact of the increased time cost coefficient on the matching success rate becomes more prominent. When the time cost coefficient is larger, even lower penalty coefficients can still achieve a matching success rate comparable to the baseline scenario.

In terms of the cost savings for passengers, the impact of individual coefficient variations on the cost savings is similar to their impact on the matching success rate, as shown in Fig. 12. Specifically, the variation in the penalty coefficient for walking time has a greater effect on travel costs, indicating that improvements in the walking environments and passengers' tolerance towards walking can significantly reduce the costs of intermodal travel. When analyzing the interaction between these two types of coefficients, it is observed that, when the time cost coefficient is low, changes in the penalty coefficient have a significant impact on cost savings. However, when the time cost coefficient is high, increasing the penalty coefficient initially leads to a decrease in overall cost savings, followed by an increase.

The carbon emissions reduction level of the buspooling system exhibits a similar trend to the matching success rate. Under a given penalty coefficient, as the time cost coefficient increases, the carbon emissions level of the intermodal system decreases rapidly. This downward trend is particularly pronounced when the penalty coefficient is high, as depicted in Fig. 13. Similarly, under a given time cost coefficient, the carbon emissions level follows a similar trend as the penalty coefficient increases. When both the penalty coefficient and the time cost coefficient are set to 50 % of the base scenario levels, the carbon emissions level reaches more than 7 tons. Therefore, improving the walking environment along transfer routes and reducing passengers' sensitivity to travel time would be effective methods for enhancing the carbon emissions reduction benefits.

Lastly, the overall benefits of the buspooling exhibit a similar trend to the carbon emissions reduction level. Under a given penalty coefficient, as the time cost coefficient increases, the overall benefits decrease rapidly. This decline is particularly pronounced when the penalty coefficient is high, as shown in Fig. 14. When both the penalty coefficient and the time cost coefficient are set at 50 % of the base scenario levels, the total benefits of buspooling reach 16,895.0 ¥and 21,608.9 ¥, respectively.

4.4. The impact of operating strategies

In the buspooling system, the operating strategies of managers can also play a significant role in shaping the potential benefits. On the one hand, the optimization objectives of the matching model consider the environmental benefits as well as the profitability level of the buspooling services. Changes in the weighting coefficients of the objectives and the fare levels can impact both the profitability level and the matching performance of this intermodal system. Based on this, city managers facing different financial situations could design more targeted fare schemes. On the other hand, the minimum passenger requirement of buspooling determines the number of vehicles deployed and the operating revenue brought in. It is a crucial parameter in modeling the intermodal system, particularly during the initial phase of market entry, where taxi passenger participation will be low and unstable. Analyzing the optimal minimum passenger requirement under different levels of passenger participation can assist managers in determining appropriate bus models and fleet sizes based on the local market scale.

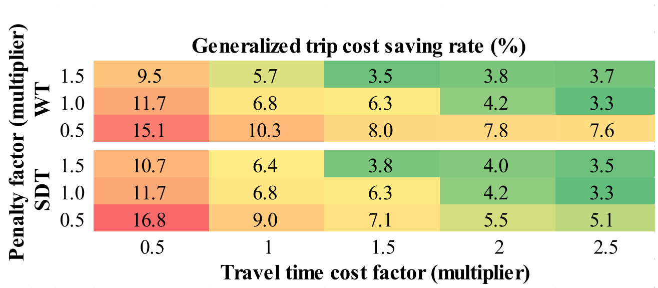


Fig. 12. Relation between travel time cost factor, penalty factor of buspooling passengers and general cost saving rate.

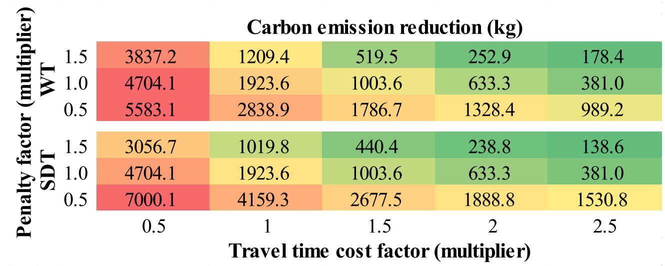


Fig. 13. Relation between travel time cost factor, penalty factor of buspooling passengers and carbon emissions reduction level.

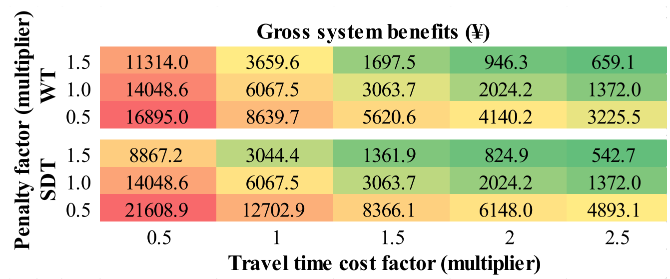


Fig. 14. Relation between travel time cost factor, penalty factor of buspooling passengers and total benefit of buspooling

4.4.1. The impact of the fare level with varying objective weights

The ratio of the weights of cost-saving benefits and operating profits in the objective function of the optimized matching model is set to 0:1, 0.25:0.75, 0.5:0.5, 0.75:0.25 and 1:0, respectively. Additionally, the buspooling and taxi fares are set to different multiples of the fares in the baseline scenario, namely (0.5, 1), (1,1), (2,1), (0.5, 1.5), (1, 1.5) and (2, 1.5). The buspooling service adopts a distance-based charging mechanism, with a baseline fare of 1 ¥ per kilometer, while taxi fares are calculated based on both the travel distance and additional charges, namely a starting fee and a charge for congestion duration.

The results of the sensitivity analysis display that, given the specific fare combinations, as the weight of cost-saving benefits in the objective function increases, the success rate of matching of buspooling shows a trend of initially rapid growth, followed by a gradual decline, as illustrated in Fig. 15. This indicates that neglecting cost-saving benefits in the objective function would lead to significant losses in the matching rate of the system. Under the given weights of the objective function, reducing the buspooling fare and increasing the taxi fare would both contribute to an improvement in the matching performance, with the latter showing a more pronounced effect. Considering both strategies, when the weights of the objectives are relatively balanced and the fare combination is set at 0.5 ¥ per kilometer for buspooling and 1.5 times the fare of the baseline scenario for taxis, the service system achieves the highest matching rate, of 8.7 %.

Statistical analysis was conducted on the operating profit level of buspooling, as illustrated in Fig. 16. Under the given ticket prices, as the

Buspooling matching rate (%)

Fare (bus, taxi)	(0：1)	(0.25：0.75)	(0.5：0.5)	(0.75：0.25)	(1：0)
(0.5,1)	2.3	4.3	4.4	4.3	4.3
(1,1)	1.8	3.3	3.4	3.3	3.3
(2,1)	0.7	1.7	1.9	1.9	1.8
(0.5,1.5)	5.9	9.0	8.7	8.5	8.5
(1,1.5)	4.9	7.6	7.7	7.5	7.3
(2,1.5)	3.0	4.9	5.4	5.4	5.3

Objective weight (distance savings : operation profits)

Fig. 15. Relation between objective weights, fare levels and matching rate of intermodal system.

Buspooling operation profits

Fare (bus, taxi)	(0：1)	(0.25：0.75)	(0.5：0.5)	(0.75：0.25)	(1：0)
(0.5,1)	786.3	310.1	463.7	310.1	191.0
(1,1)	1180.8	953.9	885.5	686.2	316.1
(2,1)	748.0	512.7	421.9	301.8	73.1
(0.5,1.5)	2068.9	1638.8	1124.3	665.7	515.3
(1,1.5)	3320.9	2837.0	2382.6	1438.0	696.9
(2,1.5)	4160.3	3708.7	3318.6	2549.0	917.2

Objective weight (distance savings : operation profits)

Fig. 16. Relation between objective weight, fare level of intermodal system and operating profit of buspooling.

weight assigned to mileage-saving benefits in the objective function increases, the operating profit of buspooling consistently decreases, but remains at a positive level. Given the predefined weights in the objective function, an increase in taxi fares significantly improves the system's operating profit, through a positive impact on the matching rate. However, at different taxi fare levels, the impact of increasing bus fares on the operating profit varies. It is observed that, as the bus fares increase, the marginal effect on the operating profit decreases, and even becomes negative. This phenomenon may be attributed to the fact that, while increasing buspooling fares can increase the profit per unit passenger, it also reduces the number of passengers participating in the intermodal system, offsetting the overall positive impact on operating profit.

The impact of the objective function weights and taxi fares on the total system revenue is comparable to their influence on the matching success rate, as illustrated in Fig. 17. Once again, it is evident that balancing the weights of mileage savings and operating profits in the objective function, along with increasing taxi fares, is advantageous for maximizing the system's total revenue.

4.4.2. The impact of minimum passenger capacity with varying participant rates

To replicate the initial market conditions of the buspooling service's launch, let us suppose that the percentage of cooperative taxi users willing to engage in the buspooling service spans from 40 % to 90 %. At the same time, we set the MinPC for buses to be between 3 and 8

Gross system benefits (¥)

Fare (bus, taxi)	(0：1)	(0.25：0.75)	(0.5：0.5)	(0.75：0.25)	(1：0)
(0.5,1)	3096.5	6807.5	6861.3	6807.5	6713.0
(1,1)	3302.7	6004.0	6067.5	5997.2	5690.1
(2,1)	1864.9	3603.4	3696.2	3641.1	3440.0
(0.5,1.5)	5113.6	11074.0	11450.9	11291.8	11168.6
(1,1.5)	6493.0	10964.9	11283.7	10933.4	10309.0
(2,1.5)	6992.5	10003.4	10339.5	10008.0	8616.6

Objective weight (distance savings : operation profits)

Fig. 17. Relation between objective weight, fare level and total benefit of intermodal system.

passengers. We can then analyze the impact of these factors on the matching performance.

The sensitivity analysis results indicate that, given the constraint on the MinPC, the matching success rate of the buspooling steadily improves with an increasing number of taxi passengers participating, as shown in Fig. 18. With a fixed user participation rate, relaxing the MinPC constraint leads to an upward trend in the matching rate, and this upward trend exhibits a significant marginal effect. When the MinPC is set to 8, the matching success rate remains below 0.5 %. However, when the MinPC is set to 3, even with a lower level of passenger participation, the matching success rate is higher than in the baseline scenario. In contrast, within the buspooling operating strategy, the impact of the minimum passenger load requirement on the matching success rate is more significant than the influence of fares. The strength of the former's impact is similar to that of the passenger tolerance mentioned in Section 4.3.

In terms of operating profit, as shown in Fig. 19, there are significant variations under different MinPCs for buspooling, as the proportion of taxi users increases. When the MinPC is set to 3, the operating profit is negative, and the higher is the user participation, the lower is the operating profit. The reason for this discrepancy needs to be explained in the context of previous matching rate results in Fig. 18. When the MinPC reduces from 4 to 3, the matching success rate shows a significant rise, generating many buspooling trips only with 3 passengers. The revenue of 3-passengers trip fare cannot cover the operating cost and then there are negative profits. Higher participation ratio of taxi users causes more 3-passengers buspooling trips, then the operating losses further widened. When the MinPC is set between 4 and 8, the operating profit is positively correlated with user participation, with the highest profit observed when the MinPC is set to 5. However, when the MinPC is set between 7 and 8, the profit level is relatively low. This may be the result of offsetting effects between the profit per unit passenger and the total number of matched passengers. From the perspective of maximizing the operating profit in buspooling, the MinPC per vehicle should be set to 5.

In terms of the overall revenue of the intermodal transit model, the revenue from buspooling shows a continuous increase as the participation rate of taxi users increases and the MinPC decreases, as shown in Fig. 20. Moreover, when the user participation rate is high, the positive impact of the MinPC constraint on the overall revenue of the buspooling system becomes more significant.

5. Discussion

5.1. Policy implications

Applying this buspooling system to the case of Beijing, we investigate the sensitivity of the matching model, considering the impact of participant preferences and operating strategies. The results can provide

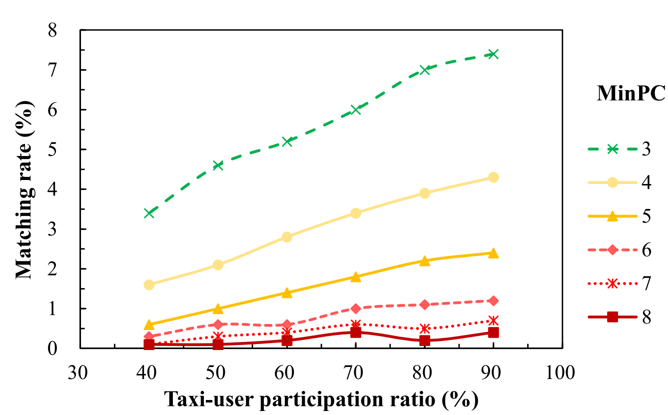


Fig. 18. Relation between participation ratio of cooperative taxi users, MinPC and matching rate.

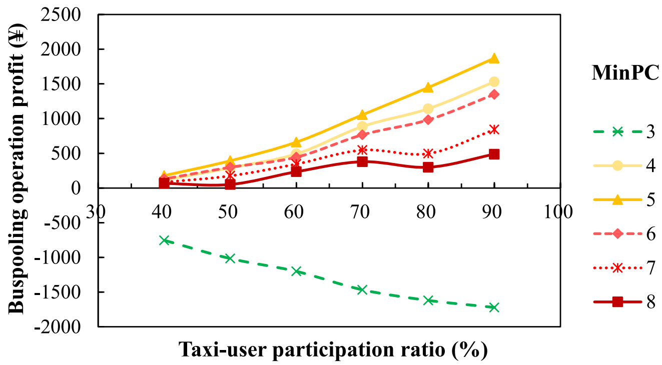


Fig. 19. Relation between participation ratio of taxi users, minimum passenger capacity of buspooling and operating profit of intermodal system.

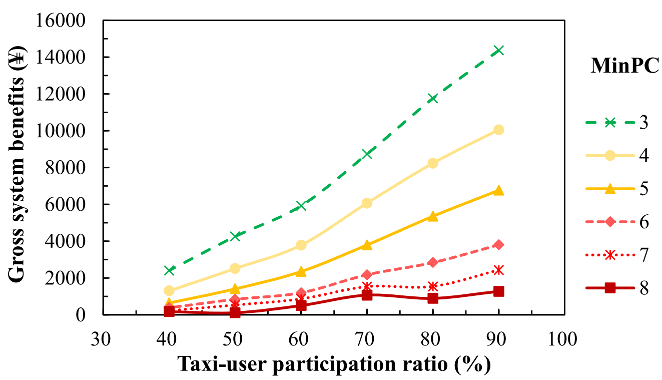


Fig. 20. Relation between participation rate of taxi users, minimum passenger capacity of buspooling and total revenue of system.

valuable insights on developing more attractive and beneficial HCRS matching system.

(1) **Where to launch buspooling services in the initial market**

In the basic scenario, we found some hot corridors for buspooling not only have a high route density but also maintain high passenger capacities on the buses. Therefore, when TNCs plan to launch buspooling services, these areas can be prioritized as initial pilot regions. In comparison, moreover, integrating buspooling services with terminal subway stations offers a higher matching rate and more significant operational advantages. Therefore, public transportation authorities should prioritize and promote this mode of transportation at such stations to maximize the social benefits.

(2) **Suggestions on reducing sharing penalty of passengers**

Sensitivity experiments on the impact of sharing penalty of passengers shows that, low-income passengers with higher tolerance on additional sharing penalty are the primary buspooling users. In light of these findings, managers should focus on the following strategies. First, improving the walking environment around intermodal service stations to enhance passengers' willingness for walking; second, promoting the intermodal transit service for work-to-home trips with less tight schedules and appropriately reducing the penalty coefficient for SDT, thereby improving the system's matching performance. These would also be effective methods for enhancing the carbon emissions reduction benefits.

(3) **Operational strategies on improving matching performances**

In the sensitivity analysis on operating strategies, reducing the taxi fare would better enhance the matching performance than increasing buspooling-subway fare. Considering the real-life situation, since December 2014, Beijing has implemented a subway fare adjustment scheme. As a result, the overall cost of intermodal travel has also increased. Therefore, in order to guarantee the share and operating profit of the buspooling, it may be a feasible strategy to appropriately increase taxi fares.

From the perspective of the choice of vehicle size, when the potential market size for buspooling is relatively small, operators should choose smaller-sized vehicles and require a lower minimum passenger load. In fact, currently, a type of customized bus operating at high-speed rail stations in Beijing only requires a minimum of 3 passengers. The MinPC per vehicle should be set to 5 to achieve the highest operating profits in the case study.

Last but not the least, the impact of the user participation rate on the overall system revenue is particularly significant. Therefore, when promoting buspooling to cooperative taxi passengers, all parties should enhance passenger participation through means such as advertising and incentives.

5.2. Limitations

There are some limitations of this study that should be discussed. First, we consider taxi passengers whose origin or destination is within the subway's service range as cooperative with the subway. However, in reality, these taxi passengers may not necessarily transfer to the subway, as their origin or destination may simply be in the vicinity of a station. Given the existing data, it is difficult to accurately determine whether a passenger is going to access the subway. Nevertheless, we can infer that taxi trips starting or finishing close to the subway are more likely to be cooperative trips. Here, we adopt this definition that was also used in previous studies. Second, it is still unclear what car commuters' attitudes are concerning the proposed carpooling mode in the real world. Hence, we do not consider the various trip costs, including the sharing psychological penalty, the detour penalty and the time deviation penalty, to be close to reality, but simply explore the impact of lower system participant numbers on the matching performance. Moreover, we neglect individual preferences and participants' socio-demographic characteristics such as gender, age and employment status when setting the parameters and constraints in our matching model. Fortunately, earlier research tends to suggest that demographic factors do not strongly influence ridesharing uptake (Canning et al., 2010; Vanoutrive et al., 2012).

6. Conclusions

To address the accessibility bottleneck of subway and further amplify the environment benefits of ridesharing, in this paper, we propose a passenger matching model for the car-users oriented HCRS, buspooling, and design an efficient algorithm to solve this problem at real-time. Taking taxi trips as a proxy for individual travel demand, we establish an online buspooling system and applying it into the Beijing metropolitan area, a series of work on travel patterns, model solutions and extensive sensitivity experiments are conducted, yielding the following valuable findings:

(1) Taxis and subway primarily have a competitive relationship, with a secondary cooperative aspect. The former are predominantly concentrated in city centers, while the latter extend towards the city outskirts. Compared with conventional cruising taxi services, ride-hailing services exhibit a more noticeable cooperative relationship with the subway, especially during rush hours and in suburban areas. Subway-extending taxi trips can facilitate access to the subway network for residents in suburban areas.

(2) In the basic scenarios, a total of 188 buspooling routes with 1049 passengers were generated, which could bring certain benefits to passengers, operators and environment. There are 41 buspooling lines that could be merged, with an average occupancy of 8.93, and this could effectively improve the bus operation's revenue level. The matching performance of buspooling access to terminal subway stations shows significant advantages.
(3) Higher costs in terms of in-vehicle time, transfer walking time, and time deviation are all detrimental to the buspooling matching performance. Passengers with lower wages or higher tolerance towards sharing penalty are likely to be the primary users. Improving the walking environment around intermodal stations may be an effective way to enhance the matching rate and the benefits in terms of reducing carbon emissions.
(4) Compared to reducing the bus fares, both raising taxi fares and setting a reasonable minimum passenger capacity would have a greater impact on enhancing the matching performance. Balancing the weights of mileage savings and operating profits in the objective is also advantageous for the system's matching performance. Using smaller-sized vehicles with a lower passenger load requirement would also be a smart strategy for the initial launching of buspooling services.

This study can be regarded as a starting point with respect to research on quantifying and enhancing the potential benefits of HCRS. More work is ahead in the future development. First, it has been found that merging buspooling lines could greatly boost the system's operating revenue. However, the associated improvement in the matching success rate and the overall social benefits is not significant. It would be interesting to explore the potential value of merging more similar lines and to determine how we might effectively leverage the advantages of combining direct bus lines and merged bus lines to improve the system's matching performance. Second, we propose a static matching mode focusing on buspooling trips within the rush hour. However, the modeling framework in this paper could easily be extended to rolling planning horizons over 24 h for various travel purposes. In this work, the model's solving time is 8 to 26 min for the base scenario, which is too long to support real-time implication. In practice, NTCs can launch buspooling services at some pilot regions in the initial market, and use more powerful servers or cloud computing platform to support the running of the App with user demand input updated by second. We believe that this work builds a solid foundation for future research on developing a practicable and sustainable buspooling system.

CRediT authorship contribution statement

Xiaobing Liu: Writing – original draft, Methodology, Writing – review & editing, Software, Conceptualization. **Yite Sun:** Visualization, Data curation, Writing – original draft, Software. **Rui Wang:** Software, Conceptualization, Writing – original draft, Methodology. **Weimin Tan:** Writing – original draft, Methodology, Software. **Feng Chen:** Supervision, Writing – review & editing, Conceptualization. **Xuedong Yan:** Supervision, Data curation, Writing – original draft, Methodology. **Yun Wang:** Writing – review & editing, Supervision, Methodology, Writing – original draft, Software.

Declaration of competing interest

The authors declare that there is no conflict of interest in any aspect of the data collection, analysis, or the funding received regarding the publication of this paper.

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