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Dynamic relocation policy for one-way electric carsharing systems considering space flexibility

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Abstract

Carsharing systems have attracted considerable market interest owing to their positive impact on resolving social and environmental pollution problems such as traffic congestion, lack of parking spaces, and greenhouse gas emissions. However, one-way carsharing systems often struggle with vehicle imbalance issues, which can affect customer satisfaction. To address this, a one-way electric carsharing model was designed to maximize operator revenue by introducing customer space flexibility. A mixed integer nonlinear program was formulated to optimize consumer flexibility, relocation, and employee-hiring decisions. The variation in the average vehicle charge at each station was captured using the state of change (SOC) model. Real data from the Evo carsharing company in Vancouver, Canada, were used to conduct numerical tests, verifying the effectiveness of the rolling horizon method in producing high-quality solutions. The results indicate that customer space flexibility can enhance the operational efficiency of carsharing systems without increasing the number of vehicles or parking spaces. This approach can also boost total system revenue and customer satisfaction, with departure space flexibility showing a significantly greater impact than arrival space flexibility.

Keywords

Location; One-way electric carsharing; Relocation; Rolling horizon; Space flexibility

Introduction

Carsharing services are increasingly popular for addressing social and environmental problems such as traffic congestion, parking demand, and air pollution (Yoon et al. 2019). Such services permit individuals to rent vehicles for short durations, paying according to the time and distance traveled (Abbasi et al. 2021). By providing convenient car access, carsharing meets personal travel demands affordably, reducing car purchases and driving kilometers (Kim et al. 2019), and lowering environmental pollution levels (Amatuni et al. 2020). Moreover, integrating electric vehicles (EVs) into carsharing fleets is accelerating the transition into clean energy vehicles owing to advancements in energy technologies and government policies, making EVs environmentally friendly and economically advantageous (Li et al. 2021).

There are three types of carsharing systems: round-trip, one-way, and free-floating (Zhang et al. 2019). The first involves a station-based system, where customers return the vehicle to the pickup station. This model has evolved into a one-way carsharing, where members can return vehicles to any parking space operated by the carsharing company. The final type allows members to pick up and drop off vehicles in a parking space in any operational area, only paying for the travel time and distance. One-way and free-floating carsharing are popular owing to their user-friendliness. This study focuses on one-way carsharing, as free-floating carsharing is not ideal for small- and medium-sized cities and presents challenges in multimodal transportation contexts.

In a one-way carsharing system, vehicle relocation is challenging and a common issue across one-way carsharing services (Hua et al. 2019). This problem arises due to the asymmetry of trip demand, leading to vehicle shortages at some stations and overstocking at others. This imbalance reduces the quality of carsharing services by hindering customers' ability to obtain or return vehicles.

Operationally, this can be addressed using user- and operator-based methods (Wang et al. 2019). The former encourages users to change origins or destinations through dynamic pricing. The latter employs staff to relocate vehicles from stations with excesses to those with shortages. As electric vehicles become more prevalent, this issue becomes more complex. Previously, carsharing operations primarily focused on vehicle relocation. Now, there is a need to address low SOCs. Unlike conventional-fuel vehicles, electric vehicles require frequent charging and have slow charging rates. Users may hesitate to use electric vehicles if they doubt their ability to convey them to their destinations. Maintaining a proper SOC during operations imposes stricter requirements on the relevant research.

This study focuses on a station-based one-way electric carsharing system. A real-time relocation policy combining operator-based and user-based methods was developed to alleviate the vehicle imbalance at each station during operation. The study's main contributions are as follows. First, it introduces an electric carsharing system with multiregional stations where staff can relocate vehicles between regions. Second, it develops an exact relocation model using the rolling horizon method and evaluates its performance through a simulation framework. Third, it integrates the concept of customer space flexibility into the operator-based relocation policy and devises a hybrid relocation policy combining operator- and user-based methods.

The structure of this paper proceeds as follows. First, the relevant literature is introduced. Then, the multiregional one-way electric carsharing relocation problem was addressed, and the rolling horizon method was utilized for resolution. A case study of the Evo Carsharing Company in Vancouver was introduced, extensively discussing the results of the numerical simulation experiments. Finally, the discussion and directions for future research are presented.

Literature review

The literature on carsharing relocation can be divided into three main categories: strategic, tactical, and operational levels (Illgen and Höck 2019). The strategic level involves infrastructure decision-making in carsharing (Correia and Antunes 2012; Correia et al. 2014). The tactical level mainly focuses on vehicle reset and reservation strategies. To address the issue of reservation time setting, Nourinejad and Roorda (2014) established a dynamic decision system using discrete event simulation. They found that setting an appropriate reservation time can reduce the fleet size. Moreover, compared to the assumption of static requirements, uncertain requirements were more consistent with real-world scenarios.

This study focuses on operational levels, specifically examining the relocation policy during carsharing system operations and driver relocation methods. Huang et al. (2020) divided research on the operation level into operation- and user-based models, both addressing vehicle imbalance issues. The former alleviates the mismatch between supply and demand by hiring drivers to relocate vehicles, whereas the latter motivates users to change their pickup and return stations. Barth and Todd (1999) proposed an initial operation-based model that predicted future demand using historical data and designed an exact relocation policy. They found that the accuracy of the demand forecast significantly influenced the effectiveness of the relocation policy. Repoux et al. (2019) proposed an estimation model based on Markov chains to predict the expected loss in future demand owing to vehicle and parking shortages. Compared with the benchmark strategy, this method improves the operational efficiency and customer service percentages. Gambella et al. (2018) designed a rolling horizon approach that divides the operating horizon (one day) of a carsharing system into smaller sub-periods, typically 15 min apart. In each sub-period, future demand for certain sub-periods is predicted to inform relocation decisions. This method leverages short-term demand forecasts, which are often more

accurate than long-term demand forecasts, to achieve approximate optimal system benefits. User-based models were initially proposed by Barth et al. (2004), who used dynamic pricing strategies to encourage users to merge or split trips. Simulation experiments demonstrate the effectiveness of the proposed strategy. Due to limited user cooperation, many scholars use dynamic pricing to influence the route arrangement of a single customer. Brendel et al. (2018) proposed a strategy that prevented users from traveling to high-supply areas and diverted them to nearby destinations.

Research on carsharing primarily focuses on fuel vehicles; however, some scholars have focused on electric carsharing systems, owing to the increasing popularity of EVs. Specialized models for electric vehicles have been developed. Yoon et al. (2019) estimated the potential electric carsharing infrastructure needs, including charger types, in Beijing using a Monte Carlo simulation. He et al. (2017) adopted a distributed robust optimization framework for the geographical area design problem of a one-way EV system, considering customer behavior and fleet management, solved using a mixed-integer second-order cone program. Weikl and Bogenberger (2015) discussed the impact of inter and intra-zone relocation on free-floating electric carsharing systems, aiming to maximize profit. Some studies have built multi-objective models by incorporating the charging and discharging processes of electric vehicles into an objective function. Boyacı et al. (2015) developed a multi-objective Mixed-Integer Linear Programming model to weigh the overall benefits of operators and customers for the location problem of one-way electric carsharing systems. Boyacı et al. (2017) designed a multi-objective optimization and discrete event simulation framework to address vehicle and staff relocation during EV-sharing operations. Other researchers examined carsharing systems through algorithms and related approaches. Li et al. (2016) proposed a continuous approximation model to obtain an approximate optimal solution to the strategic dimension problem of a large-scale electric carsharing

system. Jiao et al. (2020) designed a method for integrating price incentives and trip selection strategies to solve the operational challenges of electric carsharing systems. Gambella et al. (2018) established an accurate relocation mathematical model considering power consumption and supplementation and designed two heuristic algorithms to solve it. Considering the computational complexity of tracking the power status of each vehicle, Huang et al. (2020) designed a continuous SOC model to track the average power status of vehicles in stations. Consequently, a mixed-integer nonlinear program model was established to determine the fleet size and station capacity of a one-way electric carsharing system, which was solved using a rolling horizon optimization framework.

The study discovered that the carsharing system model concentrates on operator-based relocation research while ignoring the significant potential for consumer flexibility in relocation operations. Additionally, owing to their energy-saving and emission-reduction benefits, electric vehicles have gained significant attention in academia and industry research. Consequently, this study presents customer space flexibility for relocating vehicles and personnel in a station-based one-way electric carsharing system. The model supports the analysis of average station electricity and spatial flexibility decision-making.

Modeling

Assumptions

To maintain the feasibility and rationality of the model, we propose the following assumptions:

(1) The station infrastructure is complete, and each parking space allows vehicles to be charged. Charging begins immediately after the vehicle reaches the parking space.

(2) The initial vehicle distribution and SOC are known and optimized. This initial state is reset

daily.

(3) Stations are categorized into different areas, each with a relocated staff base. Staff can relocate vehicles from this area to other areas but must return to their regional base after completing the relocation task.

(4) The SOC of vehicles at each station follows a continuous distribution.

(5) Vehicles with higher battery power are prioritized for longer trips.

Notation

The notation used in all models is as follows:

Sets and indices

$i \in I$: set of stations, where each station belongs to a specific area

$t \in T$: set of time steps

$z \in Z$: set of zones, with each zone containing a certain number of stations

S_i: number of parking spaces at station *i*

$k \in K$: number of time steps in one horizon within the rolling horizon framework

Decision variables

E_{it}: random SOC of vehicles parked at station *i* at timestep *t*

W_{it}: number of idle vehicles at station *i* at timestep *t*.

p_{ijt}: proportion of idle vehicles at station *i* at timestep *t*.

V_{it}: number of vehicles parked at station *i* at the beginning of timestep *t*

D_{ijt}: number of served customer demands from stations *i* to *j*

$D'_{alt_{ijt}}$: number of served demands with departure space flexibility from station *i* to *j*

D'_{ialt_jt}: number of served demands with arrival space flexibility from station *i* to *j*

R_{ijt}: number of vehicles used at timestep *t* to relocate from station *i* to *j*

M_{izt}: number of drivers who move from station *i* to zone *z* at timestep *t*

n_{it}: number of vehicles at station *i* at timestep *t*

$\bar{n}_i$: number of vehicles initially configured at each station

D_{zt}: number of staff members newly allocated to zone *z* who start work at timestep *t*

DE_{zt}: number of staff members existing in zone *z* at timestep *k*, excluding new staff, D_{zt}

Functions

$f(x)$: probability density function of the SOC distribution

F (*x*): cumulative distribution function of the SOC distribution

G (*x*, *u*): recharging function, where *x* is the current SOC, and u is the charging time.

H (*x*, *u*): discharging function, where *x* is the current SOC, and u is the discharging time.

Parameters

p: income from customers renting a car per time step

c_p: penalty for refusing to serve customers.

c_e: electricity consumption cost of a vehicle running for one time step

c_r: the driving cost of relocating a vehicle for one time step

c_m: moving cost of public transportation for a single time step

c_h: hiring cost of a relocating employee for one time step

c_i: car capacity at station *i*, which represents the number of parking spaces

d_{ij}: distance from station *i* to station *j*

Q_{ijt}: actual customer demand from station *i* to station *j* at timestep *t*

α: recharging speed, SOC increase (%) per time step

β: discharging speed, SOC decrease (%) per time step

σ: the maximum working time steps of a shift

Problem setting

This section discusses the multi-region one-way electric carsharing relocation problem aiming to maximize the overall system benefit, given the number and distribution of vehicles and the location and capacity of stations. This revenue comprises serving customers revenue, vehicle electricity costs, relocation costs, staff movement costs, staff hiring costs, and customer refusal costs. This study discusses *Z* zones and *I* stations, where each zone had a series of corresponding stations and a relocator lounge. Each station has S_i parking spaces and each day is evenly divided into *T* time steps during the operation. Customer demands, denoted as Q_{ijt}, are derived from estimations or projections from station *i* to *j* at step *t*, while D_{ijt}represents the served customer demand Q_{ijt} from station *i* to station *j*. Specifically, D'_{alt_ijt} and D'_{ialt_jt} represent the served customer demand with departure and arrival flexibility from station *i* to station *j*. The model aims to optimize customer service D_{ijt}, D'_{alt_ijt}, D'_{ialt_jt} and staff relocation decisions R_{ijt} at the beginning of each time step. At the end of each time step, the state of the system, including the station, staff, and vehicle, is updated for the subsequent time step optimization.

The remainder of this paper is organized as follows: First, we established a continuous SOC mode to capture the varying average power status of each station. Then, an operator-based model is constructed to make vehicle relocation decisions and maximize the system's total revenue. Finally, we introduce departure and arrival space flexibility policies to optimize the system's efficiency.

Continuous SOC model

Unlike traditional fuel vehicles, electric-sharing systems must consider battery capacity constraints. Only vehicles with sufficient power to meet travel requirements can be used for rental or relocation. To facilitate the establishment of the electric carsharing model, we refer to the continuous SOC model proposed by Huang et al. (2020) to capture the changes in the average power status in a station. Subsequently, the main components of the continuous SOC model are summarized.

Random variable E_{it} represents the average SOC of vehicles in station *i* at timestep *t* (($E_{it} \in (0,1)$, implying that the power level ranges from 0% to 100% of the total battery power). Assume E_{it} follows a continuous distribution $E_{it} \sim D(\mu_{it}, \sigma^2(u_{it}))$, where μ_{it} and σ^2 represent the mean and variance, respectively. $f_{E_{it}}(x)$ and $F_{E_{it}}(x)$ represent the probability density function (FDP) and cumulative distribution (CDF), respectively.

$$\mathrm{G}(x,u) = \min\{x + \alpha u, 1\} \tag{1}$$

$$H(x,u) = x - \beta u \tag{2}$$

$$D_{ij_r t} + R_{ij_r t} \le V_{it}(1 - F_{E_{it}}(\beta g_{ij_r t})) - \sum_{n=r+1}^{|I|-1}(D_{ij_n t} + R_{ij_n t}) \quad \forall i \in I, r \in 1,2,... \mid I \mid -1, t \in T \tag{3}$$

$$V_{it} = W_{it} + \sum_{r=1}^{|I|-1}(Q_{ij_r t} + R_{ij_r t}) \quad \forall i \in I, r \in 1,2,... \mid T \mid -1, t \in T \tag{4}$$

$$p_{ij_r t} = (D_{ij_r t} + R_{ij_r t}) / V_{it} \quad \forall i \in I, r = 1,2,... \mid T \mid -1, t \in T \tag{5}$$

$$\mathrm{p}_{iit} = W_{it} / V_{it} \quad \forall i \in I, t \in T \tag{6}$$

$$p_{irt} = \sum_{n=0}^{r} p_{ij_n t} \quad \forall i \in I, r = 0,1,... \mid T \mid -1, t \in T \tag{7}$$

$$\eta_{ij_rt} = \int_{F^{-1}(P_{i(r-1)t})}^{F^{-1}(p_{irt})} \frac{f_{E_{it}}(\mathrm{x})}{p_{ij_rt}} x dx \quad \forall i \in I, r = 1,2,... |T| - 1, t \in T \tag{8}$$

$$\eta_{itt} = \int_{0}^{F^{-1}(p_{i0t})} \frac{f_{E_{it}}(x)}{p_{itt}} x dx \quad \forall i \in \mathrm{I}, \mathrm{t} \in T \tag{9}$$

$$\begin{aligned} u_{it+1} &= (G(\eta_{iit}, 1)W_{it} + \sum_{j \in I} G(H(\eta_{jim}, g_{jim}), \lceil g_{ijm} \rceil - g_{ijm})(\mathrm{Q}_{jim} + N_{\mathrm{jim}})) / V_{it+1} \\ \forall \mathrm{i} &\in I, t = 1,2,... |T| - 1, m = \max\{0, t + 1 - \lceil g_{ijm} \rceil\} \end{aligned} \tag{10}$$

During system operation, the SOC increases or decreases linearly with the charging and consumption of EVs. Formula (1) represents the charging process, showing a positive correlation between the SOC and charging time μ. Equation (2) represents the discharge process of the vehicle, showing a negative correlation between the SOC and travel time μ. α、β represent the percentage of the charge and discharge rate in each time step, assuming it is consistent. $G(x, \mu)$ and $H(x, \mu)$ represent the SOC of the vehicles after charging and discharging. Notably, SOC is between 0% and 100%, implying that the maximum and minimum values of $G(x, \mu)$ and $H(x, \mu)$ are one and zero, respectively.

To ensure sufficient vehicle SOC to complete the journey, a simple vehicle allocation rule is adopted, where vehicles with a large SOC prioritize providing services for long-distance travel. According to the travel time g_{ijt}, the trips starting from station *i* are arranged in ascending order of time step T. Assume j_r represent the *r*-th destination, where *r* = 1, 2, …, |*I*|-1. Therefore, we obtain Q_{ij_rt} and N_{ij_rt}, which represent the vehicles that meet the demand and the vehicles relocated from station *i* to station j_r at timestep t. Equation (3) is the vehicle SOC constraint, indicating that the number of vehicles used to travel from station *i* to station *j* cannot exceed the number of vehicles at station *i* that have sufficient electricity for the trip. $F_{E_{it}}(\beta g_{ij_rt})$ indicates the proportion of vehicles for

which the power is less than or equal to the necessary power to travel from station *i* to station *j*. $V_{it}\left(1-F_{E_{it}}\left(\beta g_{ij_rt}\right)\right)$ is used to identify the vehicles that satisfy the demand from station *i* to station j_r. $\sum_{n=r+1}^{|I|-1}\left(Q_{ij_nt}+N_{ij_nt}\right)$ indicates the vehicles above the *r* level that have been booked for long-distance travel. Equation (4) is the conservation constraint, indicating that the vehicles at station *i* at timestep *t* are idle, rented, or relocated. Equation (5) calculates the proportion of vehicles traveling from station *i* to station j_r, including relocated and rented vehicles. Equation (6) calculates the proportion of idle vehicles at station *i* at time step *t*. Equation (7) calculates the cumulative probability of vehicles for which the distance from station i to all the stations is less than or equal to g_{ij_rt}. Equations (8) and (9) calculate the average power of vehicles traveling from station *i* to station j_r at time step t.

After calculating the average electricity (AE) of the vehicles at timestep *t*, the average electricity of vehicles at each station at the beginning of timestep *t* + 1 is shown in (10). $G(\eta_{iit},1)W_{it}$ defines the AE of idle vehicles at station *i* after charging for one time step. $H\left(\eta_{jim},g_{jim}\right)$ indicates the remaining electricity after traveling a distance g_{jim}. *M* represents the departure time when the vehicle leaves station *i*. $\lceil g_{ijm}\rceil-g_{jim}$ represents the remaining time outside the driving time in one time step, which is used to calculate the charging time after driving. $\sum_{j\in I}G(H\left(\eta_{jim},g_{jim}\right),\lceil g_{ijm}\rceil-g_{jim})(Q_{jim}+N_{jim})$ represents the AE of the vehicles after the system has undergone the travel and charging process from timestep *t* to *t* + 1.

Operation-based model without flexibility

$$\sum_{t\in T}\sum_{i\in I}\sum_{j\in I}(p-c_e)D_{ijt}d_{ij}-\sum_{t\in T}\sum_{i\in I}\sum_{j\in I}c_rR_{ijt}d_{ij}-\sum_{t\in T}\sum_{i\in I}\sum_{z\in Z}c_mM_{izt}d_{ij} \quad (11)$$
$$-\sum_{t\in T}\sum_{z\in Z}c_dD_{zk}-\sum_{t\in T}\sum_{i\in I}\sum_{j\in I}c_{\mathrm{p}}(Q_{ijt}-D_{ijt})$$

$$\mu_{i1} = 1 \ \forall \mathrm{i} \in I \tag{12}$$

$$n_{it} \le c_i \quad \forall i \in I \tag{13}$$

$$\sum_{j \in I} (D_{ijt} + R_{ijt}) \le n_{it} \quad \forall i \in I, t \in T \tag{14}$$

$$D_{ijt} \le Q_{ijt} \ \ \forall i \in I, \ \mathrm{j} \in \mathrm{I}, \ t \in T \tag{15}$$

$$D_{zt} + DE_{zt} \ge \sum_{j \in I} R_{ijt} + \sum_{z \in Z} M_{izt} \quad \forall i \in z, t \in T \tag{16}$$

$$DE_{z(t+1)} = DE_{zt} + D_{zt} - \sum_{i \in z} R_{ijt} + \sum_{j \in I} M_{jzm} \quad \forall i \in I, t \in T, \\ m = \max(0, t+1-\lceil d_{jz} \rceil) \tag{17}$$

$$M_{jz\mathrm{t}} = \sum_{i \in z} R_{ijm} \quad \forall j \in I, t \in T, m = \max(0, t - \lceil d_{zi} + d_{ij} + d_{jz} \rceil) \tag{18}$$

$$DE_{it} = 0 \ \ \forall i \in I, t = 0, \sigma, ..., \lceil |T| / \sigma \rceil \sigma \tag{19}$$

$$n_{i(t+1)} = n_{it} - \sum_{j \in I} D_{ijt} - \sum_{j \in I} R_{ijt} + \sum_{j \in I} D_{jim} + \sum_{j \in I} R_{jim} \quad \forall i \in I, t = 1, ..., T-1, \\ m = \max(0, t+1-\lceil d_{ji} \rceil) \tag{20}$$

Objective function (11) maximizes the total revenue of the carsharing system. This includes revenue from serving customers minus vehicle fuel costs, relocation costs, employee movement costs of using public transit, staff hiring costs, and customer refusal costs. Constraint (12) indicates that the initial state is fully powered daily. Constraint (13) indicates that the number of vehicles parked at station *i* cannot exceed the number of parking spaces at the station. Constraint condition (14) states that the total number of vehicles used to satisfy customer demand and system relocation at site *i* in phase *k* cannot exceed the number of vehicles already at the site. Constraint (15) indicates that the number of vehicles serving a customer cannot exceed that required by the customer. Constraint (16) represents the lower limit of available employees, including existing and newly assigned employees. Constraint (17) indicates the number of employees currently in zone *z*, and M_{jzm} indicates that the driver leaves at time

m and arrives in the zone at time $k + 1$. Constraint condition (18) indicates that after the relocation operation is completed, the driver immediately returns to the original area z. Constraint (19) defines the employee's maximum working time σ. Once this limit is reached, the employees cease working. Constraint (20) outlines the calculation method for parked vehicles at station i during period $k + 1$.

Customer spatial flexibility

This model enhances customer flexibility beyond the operator-based models. Regarding customer flexibility, Ströhle et al. (2019) summarized time and space flexibility, using them to optimize the performance of a round-trip carsharing system. There remains limited research on customer flexibility regarding the operational dimension of one-way carsharing. The literature on user-based methods often regards customer demand as a function of service prices, optimizing system operations by influencing prices. However, this method is often difficult to use practically owing to the lack of relevant data. This section introduces customer space flexibility, which enables customers to choose nearby locations close to the target station for picking up or exchanging cars. This process, involving the hiring of employees to relocate cars, is referred to as the operator-based and user-based hybrid method.

As shown in Fig. 1, spatial flexibility manifests in two main aspects: origin and destination flexibility. First, an alternative station is identified for each station, typically the nearest one. Using the following figure as an example, A: (3,5) indicates three available vehicles and five parking spaces at station A. Station B, being the nearest station to A, serves as its alternative station. Similarly, the alternative station of D is station E. The spatial flexibility of the origin allows an alternative station to provide vehicles to meet travel demands when the number of vehicles in the main station is insufficient. Assuming a demand for four vehicles from Station A to Station D but availability of three,

the vehicles cannot fully meet the travel demand. The spatial flexibility of the origin allows customers to use the alternative Station B to provide services. At this time, Station B can provide one vehicle to meet the demand. The spatial flexibility of a destination indicates the use of an alternative station when the main station's parking space is insufficient. Assuming there is a demand for five vehicles from Station A to Station D, both Stations A and B have five available vehicles, and the available parking spaces at Station D are only four, the demand cannot be met. However, spatial flexibility allows the operator to use an alternative Station E to provide the necessary services. At this time, the demand can be satisfied by providing one parking space at station E.

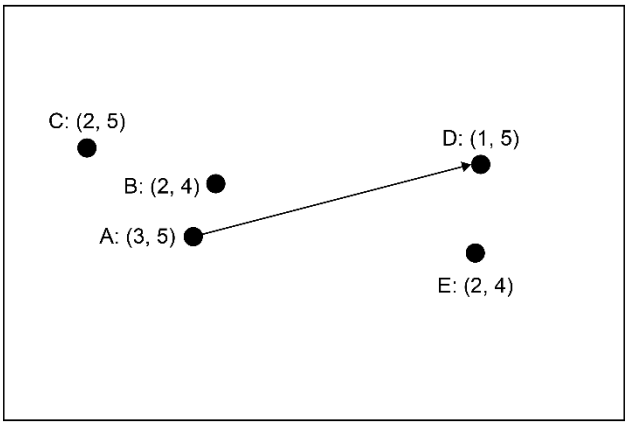


Fig. 1 Customer space flexibility

Therefore, the original model requires modification to describe these characteristics. The first step involves considering the available vehicle constraints for each station. It is necessary to expand the number of vehicles available at the original single station to include the total number of vehicles at the main station and its alternative stations. Let alt_i represent the alternative station of station i, and let D'_{ijk} denote the demand satisfied from station i to station j when station i is used as the alternative station. Constraint (13) is replaced with the following formula:

$$\sum_{j\in I}(D_{ijk}+R_{ijk}+D'_{ijk})\le n_{ik}\ \ \forall i\in I,k=t,...,t+K-1 \tag{21}$$

Second, the demand constraint must be expanded from the demand between two separate primary stations to that between primary and alternative stations. Constraint (14) can be rewritten as follows:

$$D_{ijk}+D'_{alt_i jk}\le Q_{ijk}\ \ \forall i\in I,\ \mathrm{j}\in \mathrm{I},\ t\in T \tag{22}$$

$$D_{ijk}+D'_{ialt_j k}\le Q_{ijk}\ \ \forall i\in I,\ \mathrm{j}\in \mathrm{I},\ t\in T \tag{23}$$

As illustrated below, the formula for determining the number of vehicles in different periods also changes.

$$\begin{aligned} n_{i(t+1)} &= n_{it}-\sum_{j\in I}D_{ijt}-\sum_{j\in I}D'_{ijt}-\sum_{j\in I}R_{ijt}+\sum_{j\in I}D_{jim}+\sum_{j\in I}D'_{jim} \\ &+\sum_{j\in I}R_{jim}\ \ \forall i\in I,t=1,...,T-1,m=\max(0,t+1-\lceil d_{ji}\rceil) \end{aligned} \tag{24}$$

Solution algorithm

The original model has nonlinear constraints (2)–(9), making it difficult to solve using commercial solvers like Cplex or Gurobi. To address this, the rolling horizon method, widely used to overcome computational pressures, has been developed (Liang et al. 2018). When the number of vehicles and parking spaces is known, the model must make decisions regarding the served demand D_{ijk}, relocations R_{ijt}, vehicle distribution n_{it}, and relocators D_{zk} for each time step. As shown in Fig. 2, the optimization framework divides a day into *T* equal horizons, referred to as time steps. For each timestep *t*, the input is the customer demand for the next *K* time steps, and the output is the optimal decision of timestep *t* obtained by solving the horizon t mathematical program. After calculating the car-sharing system status in period *t* + 1 according to the decision at timestep t, the existing status is

used as the input to the horizon (t + 1) mathematical program to obtain the optimal decision for period *t* + 1. This procedure iterates from *t* = 0 to *t* = *T*, known as the rolling horizon method.

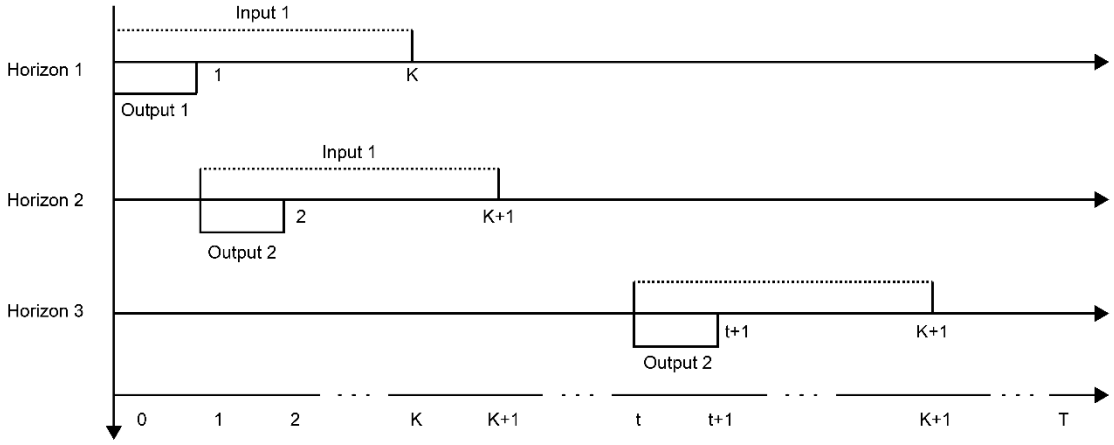


Fig. 2 Framework of rolling horizon method

In horizon *t*, the input data include the number of parking spaces c_i in all periods, the available vehicles n_{it} and the average power μ_{it} in period *t*, the demand from timestep *t* to *t* + *K* - 1, and the decisions D_{ijm}, R_{ijm}, M_{izm} and D_{zk},$\forall i,j \in I, m < t$. The output data are essential variable decisions in period *t* when the system benefits from timestep *t* to timestep *t* + *K* - 1 are maximized: D_{ijt}, R_{ijt}, M_{izt} and D_{zt}. The carsharing operating model for time *t* is as follows:

$$\begin{aligned}\max\ & \sum_{k=t}^{t+k-1}\sum_{i\in I}\sum_{j\in I}(p-c_e)D_{ijk}d_{ij}-\sum_{k=t}^{t+k-1}\sum_{i\in I}\sum_{j\in I}c_rR_{ijk}d_{ij}\\ &-\sum_{k=t}^{t+k-1}\sum_{i\in I}\sum_{z\in Z}c_mM_{izk}d_{ij}-\sum_{k=t}^{t+k-1}\sum_{z\in Z}c_dD_{zk}\\ &-\sum_{t\in T}\sum_{i\in I}\sum_{j\in I}c_{\mathrm{p}}(Q_{ijk}-D_{ijk})\end{aligned} \tag{25}$$

$$\mu_{i1}=1\ \forall i\in I \tag{26}$$

$$n_{ik}\le c_i\quad \forall i\in I \tag{27}$$

$$\sum_{j\in I}(D_{ijk}+R_{ijk})\le n_{ik}\quad \forall i\in I, k=t,...,t+K-1 \tag{28}$$

$$D_{ijk} \le Q_{ijk} \quad \forall i \in I,\ \mathrm{j} \in \mathrm{I},\ t \in T \tag{29}$$

$$D_{zk} + DE_{zk} \ge \sum_{j \in I} R_{ijk} + \sum_{z \in Z} M_{izk} \quad \forall i \in z, t \in T \tag{30}$$

$$DE_{z(k+1)} = DE_{zk} + D_{zk} - \sum_{i \in z} R_{ijk} + \sum_{j \in I} M_{jzm} \quad \forall i \in I, k = t, ..., t + K - 2, \\ m = \max(0, k + 1 - \lceil d_{jz} \rceil) \tag{31}$$

$$M_{jzk} = \sum_{i \in z} R_{ijm} \quad \forall j \in I, k = t, ...t + K - 2, m = \max(0, k - \lceil d_{zi} + d_{ij} + d_{jz} \rceil) \tag{32}$$

$$DE_{ik} = 0 \quad \forall i \in I, k = 0, \sigma, ..., \lceil |T| / \sigma \rceil \sigma \tag{33}$$

$$n_{i(k+1)} = n_{ik} - \sum_{j \in I} D_{ijk} - \sum_{j \in I} R_{ijk} + \sum_{j \in I} D_{jim} + \sum_{j \in I} R_{jim} \\ \forall i \in I, k = t, ..., t + K - 2, m = \max(0, k + 1 - \lceil d_{ji} \rceil) \tag{34}$$

By solving the model, we can obtain the served demand D_{ijt}, number of relocated vehicles R_{ijt}, return number of drivers M_{izt}, and number of drivers D_{zt} in period *t*. Using these output data, the average power μ_{it+1} of each station at the initial timestep *t* + 1 can be calculated by Formula (10). Similarly, the available vehicles n_{it+1} at each station during timestep *t* + 1 can be calculated using Equation (34). Subsequently, the input data in timestep *t* + 1 are updated while importing the horizon *t* mathematical model to obtain the optimal decision and output data in time step *t* + 1. The program iterates until all horizons *T* are considered. The total profit is calculated according to the optimal decisions regarding D_{ijt}, R_{ijt}, M_{izt} and D_{zt} obtained by solving the horizon *t* model for each time step.

Application

Setting up the case study

Real data from Vancouver, Canada, were used for verification. The data include demand, operation,

and infrastructure data. The demand data were obtained from the real data from the Evo Corporation.

Figure 3 represents the distribution of the average travel demand in different time steps, with 25,584 data points selected from March 7, 2018, to March 13, 2018. The X-axis represents the time from 0:00 to 24:00, and the Y-axis represents the total travel demand for a week in the corresponding period. By observing the travel situation at different time steps, significant fluctuations in travel demand were evident throughout the day, including three main peak and one trough periods. The peak periods were 7:00–8:30, 12:30–14:30, and 16:00–20:00, while the trough period was from 23:00 on one day to 5:00 on the next day. It can be inferred that during these peak travel periods, the electric carsharing system experienced greater operational pressure, necessitating stricter fleet management requirements.

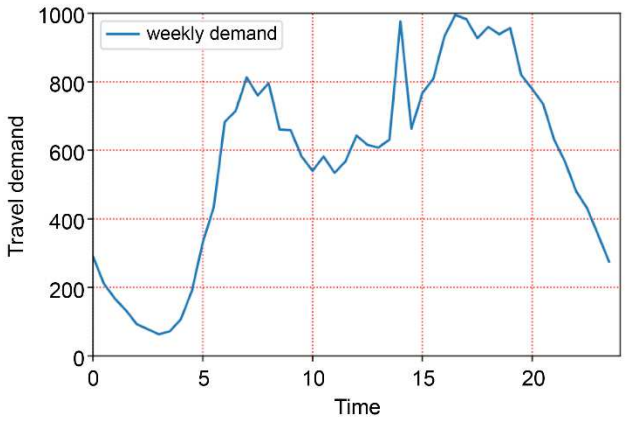


Fig. 3 Fluctuations in customer demand throughout the day

Figure 4 presents the distribution of 52 carsharing stations and 1020 vehicles. The location and size of each point represent the station location and its initial number of vehicles, respectively. Larger dots indicate stations with higher vehicle counts and greater capacity. Considering that the station capacity is unknown and the number of vehicles in the initial state of the station is known, it is assumed

that the number of parking spaces is a multiple of the initial number of vehicles (i.e., 2.5) (the final number of parking spaces was obtained by rounding up). The relocation operation involves two parts: real-time and daily relocation. The former relocates at each time interval to alleviate the vehicle imbalances. The latter resets the vehicle distribution to the initial state of the day at the last time step. This initial state is assumed to be the optimal vehicle distribution.

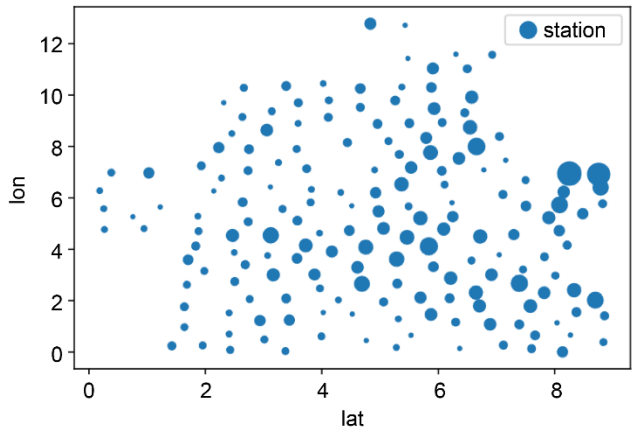


Fig. 4 Distribution of carsharing stations

The operation data (Table 1) by Huang et al. (2020) include customer profit p, fuel c_f and electricity consumption costs c_e, driving c_d and moving costs of relocation c_m, and hiring costs c_h. The penalty c_p=15 RMB is set for trip refusal to compensate for customer dissatisfaction. The charging and discharging speeds assume that the specifications of the vehicles and charging piles are identical, and that the speed of power consumption and replenishment is unaffected by external conditions. The charging speed α = 25% means that continuous charging over a time step increases vehicle power by 25% of the total capacity (if not already full). The discharge speed β = 16.67% indicates that the power consumption of the vehicle is 16.17% of the total power capacity per time step.

Table 1. Model parameters.

Parameter	c_r	c_e	c_h	c_m	c_p	p
Value	34	20	20	10	15	114
Unit	RMB/h	RMB/h	RMB/h	RMB/h	RMB/trip	RMB/h

We set a 24-hour weekday operational schedule for the electric carsharing system, divided into 48 equal time intervals of 30 min each. Additionally, the demand data for one day are generated according to historical travel records. Assuming that the demand of the simulation experiment is set to *n*, a piece of travel data is randomly selected from the database and added to the demand dataset (the data in the original database remained intact, and this operation was repeated n times).

Optimization results

Carsharing demand–service ratio

Using the percentage of served demand as a key indicator for measuring the operation of the carsharing system, a preliminary analysis is conducted to study the shortage of vehicles at different times. In Fig. 5, the x-axis represents the time step, while the y-axis represents the service rate. The results show that the average service rate of this test is 73.6%, and the service rate is above 65% most of the time. Furthermore, the low service rate period occurs mainly during the morning and evening peaks, which is caused by the concentrated number of homogeneous demands. During the morning peak, there is a notable surge in demand from the suburbs to the urban areas, resulting in a shortage of vehicles in the suburbs and insufficient parking spaces. Conversely, during the evening rush hour, high demand shifts from the urban area to the suburbs, resulting in parking space shortages in the suburbs and vehicle

deficits in urban areas.

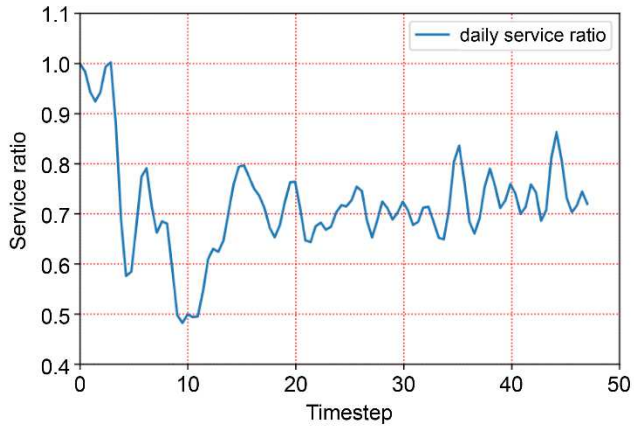


Fig. 5 Service ratio throughout the day

Table 2 presents the percentage of served demands for trip requests of different lengths. Considering that the maximum distance between two stations in this experiment is 13.19 km, we divide the results into eight groups, namely, 0–1, 1–2, 2–3, 3–4, 4–5, 5–6, 6–7, and ≥7 km. The results show that the service rate of trips of 1–2 km was the lowest at 58.54%, whereas the service rate of trips of more than 2 km was greater than 70%. Above 2 km, the customer service rate increases with travel distance. Thus, long-distance trips are high-value targets for carsharing systems, and providing services to them can yield greater benefits.

Table 2. Service ratio for different travel distances

Travel distance	0-1	1-2	2-3	3-4	4-5	5-6	6-7	≥7
Service ratio	67.27%	58.54%	71.94%	73.46%	75.62%	78.97%	75.45%	79.19%

Relocation policy and horizon period

This section discusses three distinct relocation policies: real-time, rolling horizon, and precision. Setting the daily demand to 4000, experiments are conducted on three relocation policies, and the performance of the rolling horizon policy under different horizon periods, *K (the input period of the rolling horizon policy in one iteration)*, is discussed. Table 3 summarizes the optimization results, revealing that the exact policy outperforms the other two policies in terms of service rate, number of relocations, and profit. This shows that reasonable relocation can increase the efficiency and profit of the system operation, consistent with findings from previous research. Although the exact policy can obtain higher-quality solutions, future demand is difficult to predict in the real world; therefore, this study considers future demand as the upper limit of the optimization result. The real-time strategy service rate and profit are the lowest; however, the corresponding solution time is the shortest. Particularly, the real-time strategy involves zero relocations, indicating its shortsighted, greedy policy is unsuitable for alleviating vehicle imbalance issues. A practical strategy is the rolling strategy, whose service rate, profit, and solution time are located between those of the exact- and real-time policies. The key parameter *K* in the rolling horizon policy represents the future customer demand period predicted by each iteration of the algorithm. As *K* increases, the algorithm's service rate and profit approach those of the exact strategy more closely, albeit at the cost of longer solution times. Thus, the rolling horizon policy must balance the solution's quality and time to obtain the most effective results. In this study, *K* is set to five in the subsequent numerical verification to save time.

Table 3. Optimization results of different algorithms

	Real-time	K=5	K=10	K=15	Exact
Satisfied demand	2379	2503	2530	2627	2963
Relocation	0	46	56	124	435
service rate	79.1%	83.43%	84.33%	87.60%	98.77%
Revenue	40176.19	44083.40	44599.61	46046	50252.12
Relocation cost	0	148.00	233.40	424.12	508.67
Movement cost	0	63.13	100.40	200.79	278.01
Hiring cost	0	400	560	1120	720
Profit	40176.19	43472.28	43715.81	44301.84	48745.45

Verification of space flexibility

The notion of space flexibility is introduced, and the initial model is extended to analyze the performance of carsharing systems under four scenarios: normal, departure flexibility, arrival flexibility, and full space flexibility. To evaluate the operation of the carsharing system, key performance indicators are considered, including the number of satisfied demands, number of relocations, service rate, total revenue, compensation cost, net profit, and average SOC.

Table 4 shows that with a flexibility cost of 20, departure flexibility increases the service rate of the system by 2%, reduces the number of relocations, and increases net profit. Departure flexibility is combined with arrival flexibility to achieve complete space flexibility.

Table 4. Customer space flexibility effect

	Normal	Departure flexibility	Arrival Flexibility	Complete flexibility
Satisfied demand	2093	2138	2092	2160
Relocation	50	37	39	31
Service rate	69.76%	71.327%	69.73	72.03%
Revenue	37226.38	38411.07	37452.40	39151.78
Relocation cost	131.57	136.74	129.35	103.35
Movement cost	69.01	64.11	68.18	52.30
Hiring cost	480	400	400	320
Profit	36545.79	36950.23	36154.87	36756.13
Average SOC	85.91%	85.46%	85.30%	85.15%

Sensitivity analysis

System performance under various recharging speeds

We tested the performance of the EV system at charging rates of 12.5%, 25%, 37.5%, and 50% per time step. Additionally, other parameters, such as setting the discharge speed to 16.67% and the time step interval to 30 min, remained consistent with the parameter setting table. The optimization results are presented in Table 5.

Table 5. Effect of charging rate

α (per time step)	Profit	Satisfied demand	Vehicle relocations	Average SOC
0.125	48065.08	70.23%	41	74.00%
0.25	49223.32	72.43%	61	81.14%
0.375	49875.63	73.5%	61	85.31%
0.5	50846.74	74.8%	71	88.14%

The table above shows that increasing the charging speed at the charging pile enhances the operation of the carsharing system, leading to higher revenue, customer service rates, and average SOC. As the charging rate increased from 12.5% to 50%, revenue increased from 48065.08 to 50846.74, and the customer service rate increased from 70.23% to 74.8%. A faster charging rate reduces the number of trips declined in the carsharing service owing to power constraints. Ultimately, with infinite fast charging rates or widespread battery replacement technology, the operating efficiency of the electric carsharing system is equivalent to that of the fuel vehicle system, offering more energy-saving and environmental protection advantages. Notably, the costs of different charging rates are not considered in this study. Generally, faster charging rates imply higher costs, which tend to grow exponentially with increasing charging rates. In practical applications, selecting charging piles with appropriate specifications is crucial to maximizing actual revenue.

System performance under different shift hours

We explore the impact of relocating workers' shift-hour changes on a carsharing system with shift

hours of two, four, six, and eight hours. Assuming that the daily customer demand is 4000 and other parameters take their default values, the results are shown in Table 6.

Table 6. Effect of shift hours

Shift-hour	Profit	Satisfied demand	Vehicle relocations	Average SOC
8	37423.81	73.5%	60	85.94%
6	37363.39	74.46%	89	85.20%
4	37394.96	74.63%	132	85.57%
2	37297.87	75.87%	163	83.17%

The above table shows the performance of the system under varying shift-hour values. Performance indicators include profit, satisfied demand, vehicle relocation, and average SOC. As shift hours decrease from 8 h to 2 h, profit and average SOC show a downward tendency and satisfied demand and vehicle relocation gradually increase by 2.37% and 103%, respectively. The average SOC fluctuates slightly. The reduction in shift hours optimizes vehicle distribution by increasing the number of vehicle relocations, significantly improving satisfied demand; however, the profit fluctuates owing to increases in relocations. Profits increase when the benefits from relocation operations exceed relocation costs, and vice versa. A shorter shift time results in a smaller average SOC. This is because frequent relocations increase the power consumption of the system, thereby decreasing the average SOC over time.

Managers must set shift hours according to their needs. When considering factors such as

satisfied demand, and relocation and electricity costs comprehensively, a four-hour shift is optimal. However, to maximize customer satisfaction, shift hours should ideally be minimized to two hours.

System performance under different time step sizes

This section examines the impact of time step values on system performance. We evaluate the time step values at 15 and 30 min, assuming that the daily demand is 4000 and the other parameters take their default values. The results are shown in Table 7.

Table 7. Effect of the time step size

Demand	Time steps =15			Time steps =30		
	Profit	Satisfied demand	Average SOC	Profit	Satisfied demand	Average SOC
3000	21337.29	81.8%	75.48%	23634.71	84.17%	81.72%
4000	45246.98	79.18%	70.63%	42079.99	78.2%	77.40%

The above table illustrates the effect of different time step values on the system performance, focusing on profit, satisfied demand, and average SOC. Reducing the time step from 30 min to 15 min increases the average profit and satisfied demand, demonstrating that the smaller the time step, the more refined the operation of the system and the more customers served to obtain greater benefits. This is accompanied by an increase in energy consumption. Although a smaller time step yields superior optimization results, we employ a time step of 30 min owing to the computational burden of the numerical experiments. Notably, the algorithm in this study can be applied to any time step; however, a

smaller time step entails a greater computational expense.

Conclusion

In this study, a station-based one-way electric carsharing model was proposed to investigate the role of space flexibility in carsharing systems, including departure space flexibility and arrival space flexibility. This model employed the net profit of the system as the objective function, considering the customer service rate and vehicle power, and iteratively optimized vehicle service decisions, relocation decisions, staff scheduling decisions, and spatial flexibility decisions. A rolling horizon algorithm was developed and validated using large-scale data from Vancouver, Canada. The sensitivity analysis examined the impacts of different charging rates, employee shift hours, and time step sizes on system operations.

Numerical experiments demonstrated that spatial flexibility can improve operational efficiency without increasing the fixed assets of the carsharing system, such as total revenue and service rate. Notably, departure space flexibility proved more cost-effective and yielded superior results compared with arrival space flexibility. Additionally, the complete space flexibility strategy encompassed both departure space flexibility and arrival space flexibility, and had superior performance. Considering the greater difficulties presented by complex relocation operations, managers can implement departure space flexibility to improve system efficiency when operations are constrained.

Although operator-based relocation considers customer flexibility, several aspects require further investigation. The current model's customer flexibility primarily considers only space flexibility, which represents incomplete flexibility. In the future, we intend to establish a completely spatiotemporally flexible model for vehicle relocation to investigate its performance potential. Additionally, customer

flexibility is reflected in alternative stations, and a dynamic pricing strategy can broaden the scope of the alternative stations. The impact of dynamic pricing on customer demand and system revenue should also be explored further.

Declarations

Ethics approval and consent

Not applicable

Data availability

The datasets used and analysed during the current study are available the following trace repository: http://netlab.ice.ufjf.br/index.php/carsharingdata/.

Author contributions

Ronghang Jiang spearheaded the research design, oversaw data collection, conducted the primary data analysis, and led the writing and revision of the manuscript. Qiang Su provided expertise in the theoretical framework of the study, reviewed and provided feedback on the manuscript, and assisted in the interpretation of results. Lei Zhu was responsible for the literature review, contributed to the methodology section, and provided critical insights during the revision process. Wei Yang contributed significantly to the data analysis, and participated actively in the writing and editing of the manuscript.

Competing interests

The authors have no competing interests to declare that are relevant to the content of this research.

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