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Exploring influential factors of fleet and parking management in shared autonomous vehicle systems: An agent-based simulation framework

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ABSTRACT

Shared autonomous vehicles (SAVs) are expected to enhance urban transportation efficiency through innovative mobility resource management. By developing a comprehensive agent-based simulation framework, this study investigates several key factors influencing fleet size and parking demand for the adoption of SAVs in future urban mobility systems. The framework evaluates how both operational factors (e.g., reservation time and maximum waiting time) and demand-side characteristics (e.g., demand rate and the balance between trip origins and destinations) jointly affect the performance of the SAV system. It uses a two-stage simulation process that includes capacity estimation and performance evaluation. In the initial warm-up stage, the simulation estimates the fleet size and parking spaces needed to serve specific travel demand. These initial estimates are then used in the second stage to run further simulations and assess additional performance indicators, including final required parking spaces, empty meters traveled, and trip rejection rate. To obtain a holistic understanding of the studied factors, we construct various simulation scenarios based on historical taxi data in central areas of Chengdu, Shanghai (China), and Manhattan of New York City (USA), and build structural regression models on the simulation outcomes. The results reveal a general mechanism by which operational characteristics and demand patterns influence SAV fleet and parking sizes. We find that a 1 % increase in overall travel demand results in about a 1 % increase in the number of SAVs needed and required parking spaces. Meanwhile, a 1 % improvement in the balance of origin-destination (OD) trips, which reduces spatial mismatches between vehicle supply and trip requests, can help offset the need for additional vehicles and parking spaces. These findings offer critical policy implications, emphasizing the need for integrating SAV deployment with land-use strategies, balancing fleet investment, environmental costs, and service quality (e.g., lower waiting time) in SAV planning and operations.

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1. Introduction

The rapid development of vehicular and communication technology has brought shared autonomous vehicles (SAVs) into people's lives. Cities like Phoenix and San Francisco in the United States, and Beijing and Shanghai in China are at the forefront, implementing SAVs on a trial basis (Wong and Shaheen, 2020; Liu et al., 2022a,b; Miller, 2022; Bahk et al., 2024; Zhang et al., 2024; Hu et al., 2025b; Wang et al., 2025). In an SAV system, self-driving vehicles are shared among users. The introduction of SAVs is expected to reduce the total number of cars and required parking spaces in the city but at the cost of more empty travel, which includes pickup trips and cruising trips for passenger search (Zhang et al., 2015; Golbabaei et al., 2020; Yan et al., 2020; Kumakoshi et al., 2021). Hence, the introduction of SAVs raises several new questions and challenges for cities: (1) How to estimate the desired fleet size and parking demand for SAVs while taking into account preferences from different stakeholders such as users, fleet operators and cities? (2) How to design the system to reconcile the induced empty travel and demand satisfaction? (3) What are the major influential factors of the fleet and parking space management and the overall system performance? (4) How do all the above context-specific variables relate to the city size and urban layout? These are also the main research questions addressed in this study.

A number of studies have explored the fleet and parking management of SAVs (Spieser et al., 2014; Kondor et al., 2020; Li et al., 2025; Hu et al., 2025a). However, previous works often investigate the fleet size and parking spaces independently. In fact, fleet size directly affects parking demand and usage patterns (Okeke, 2020; Golbabaei et al., 2020; Winter et al., 2020; Xia et al., 2021). Conversely, it has been shown that a reduction in parking spaces leads to increased vehicle miles/kilometers traveled (VMT/VKT), largely due to extensive empty trips (Kondor et al., 2018; Zhang and Wang, 2020). Therefore, it is crucial for both the service operator and the policymaker to recognize and understand the trade-offs among fleet size, parking spaces, and the resulting empty meters traveled by SAVs, to maximize system efficiency. On the other hand, while some studies have examined the influential factors of optimal fleet size and parking demand of SAVs, they often focus on a single factor and discuss its impact on either fleet size or parking capacity (Xiao et al., 2018; Xiao and Xu, 2022). In addition, the analyses are mostly limited to a single urban context (Boesch et al., 2016; Ma et al., 2017). However, fleet size and parking demand of SAVs are jointly influenced by factors that range from travel demand patterns and operational characteristics (Zhang et al., 2015; Melendez et al., 2020; Choi and Lee, 2023). Such influences may also vary across cities with different structures and layouts (Tachet et al., 2017; Milakis et al., 2018; Van Brummelen et al., 2018).

This study aims to bridge these gaps by investigating the key factors that determine the fleet size and parking spaces in an SAV system and how their influences are shaped by the urban structure and layout. To this end, we develop an agent-based simulation of SAV service and propose a two-stage simulation framework, comprising a warm-up stage and a performance evaluation stage. In the first stage (warm-up), the simulation dynamically introduces vehicles and parking spaces to serve all orders without rejections, resulting in an estimated fleet size and initial parking configuration. In the second stage, using the fixed fleet size and parking allocation from the first stage as a starting point, further parking spaces are allowed to be introduced as needed to ensure operational feasibility and evaluate performance indicators, including final parking spaces, empty meters and trip rejection rate. This two-stage process ensures that both fleet and parking needs are assessed under realistic operational conditions. In the experiments, we construct simulation scenarios using the taxi data in the central urban areas of Chengdu and Shanghai in China, and Manhattan of New York City in the United States. These selected cities have distinct urban layouts and demand patterns. Incorporating real-world taxi trip data, the agent-based simulation generates city-specific results, allowing for detailed evaluation of how operational settings (e.g., reservation time, maximum waiting time) and demand patterns (e.g., origin-destination (OD) demand balance) influence system design and performance. Based on the taxi data, we further simulate various demand profiles with different demand levels and OD balance in each city, and also include several operational characteristics as input parameters. To quantify the effects of operational and demand-side factors, we employ a regression-based structural equation modeling (SEM) framework. This approach not only estimates the direct effects of each factor but also captures the interdependencies and mediated relationships among simulation outcomes — namely, fleet size, parking spaces, and empty meters — providing a more comprehensive understanding of SAV system dynamics. The main findings of this study are summarized as follows:

- Simulating empirical taxi demand data under varied reservation and maximum waiting times, we identify a general influence mechanism of travel demand patterns and operational characteristics on the SAV fleet and parking sizes and the system efficiency. Specifically, a higher demand rate, lower OD balance, shorter reservation time, and shorter maximum waiting time require a larger number of vehicles and parking spaces. Among the studied cities, the service rate is between 1 and 3 trips per vehicle per hour. Based on the estimated fleet size and parking spaces, the required parking spaces per vehicle range from 0.4 to 1.0 in Chengdu and Manhattan (NYC), and 0.3 to 1.1 in Shanghai.
- The structural regression analysis shows that operational and demand-side characteristics jointly shape fleet size, parking demand and performance in the SAV system. Specifically, a 1 % increase in travel demand results in approximately a 1 % increase in fleet size, parking spaces, and empty meters. Meanwhile, a 1 % improvement in OD balance can help offset the need for additional vehicles and parking spaces as well as the increased empty meters. The findings highlight the importance of integrating SAV planning with land-use strategies—such as mixed-use development and job-housing balance—to encourage more balanced OD demand patterns and subsequently enhance overall system efficiency.
- The study also observes a trade-off between fleet size and empty meters in SAV operations. In particular, extending reservation time and relaxing maximum waiting time constraint can reduce the required fleet size and thus lower capital costs. Meanwhile, these adjustments in the operational parameters raise empty meters directly and indirectly through the mediated effects of fleet size, leading to additional energy consumption and emissions. Thus, strategies that prioritize fleet minimization alone are insufficient

for efficient SAV deployment. The findings suggest the need for designing operational and regulatory strategies that balance fleet investment and environmental costs.

The remainder of this paper is organized as follows. In Section 2, we review the relevant literature and summarize the research gaps. Section 3 presents the simulation framework and its main modules. The research methodology is detailed in Section 4. In Section 5, we first give a brief introduction to the dataset, then report the simulation results and generalize the main insights. Finally, Section 6 provides policy implications and Section 7 concludes this study and offers several directions for future work.

2. Literature review

Over the past decade, studies on SAVs have attracted growing interest in transportation research, covering a wide range of topics (Fagnant and Kockelman, 2014; Krueger et al., 2016; Narayanan et al., 2020; Huang et al., 2024a,b). Since our focus in this study is fleet and parking management, along with their influential factors, we focus on reviewing studies highly relevant to this topic, see a summary of some representative studies in Table 1. For a broader review on SAV and more generally, ride-hailing services, the readers are kindly referred to Wang and Yang (2019).

2.1. Fleet sizing and parking in SAV systems

The SAV fleet management problem has been studied extensively in the literature using either analytical or simulation-based models under a wide range of settings and arriving at results with widely different operational characteristics (Spieser et al., 2016; Vazifeh et al., 2018; Seo and Asakura, 2021). In general, analytical models formulate the fleet sizing problem in an optimization framework. For instance, Ma et al. (2017) estimated the optimal fleet size by modeling the trip sequence of each AV and optimizing the trip sequences with minimum operational cost via a linear program. It is concluded that 93 vehicles are sufficient to serve over 1168 trips defined in the test scenario, that is, the trip-to-vehicle ratio is over 10. As an extension, Narayanan et al. (2022) optimized the SAV trip sequences in a mixed traffic system along with private vehicles. Road users, including private vehicle and SAV users, and the SAV operator are two players in the system. Road users aim to minimize their personal total travel costs and the SAV operator aims to minimize the total operating costs to be covered by the company through SAV trip sequence optimization and coordination. The optimal solution is gained by reaching a Nash Equilibrium. With a planning horizon of six hours, their results showed a trip-to-vehicle ratio of 2.2 and 2.6 under 10 % and 20 % penetration rates of SAVs for the Sioux Falls network, respectively. Fan et al. (2023) further considered mode choice and congestion effects in the system and developed a mixed-integer non-linear programming model to solve for profit-maximizing SAV fleet size. Specifically, travelers choose between SAV and cycling following a binary logit model and the travel times are flow-dependent. By testing multiple scenarios with varying operational costs and pricing rates of SAV service as well as different traffic conditions, the study estimated the penetration of SAV service and required fleet size during one morning peak hour. The trip-to-vehicle ratio ranges from 1.3 to 1.5 in these scenarios.

Compared to analytical models, simulation-based models offer more flexibility for modeling the complex demand-supply interactions in the SAV system (Jing et al., 2020). Fagnant et al. (2015) utilized an agent-based simulation to determine a desired fleet size to serve the travel demand on a typical weekday in Austin, Texas. The fleet size is determined in a progressive way: a new SAV is generated when a passenger has been waiting for 10 minutes. Finally, it is found that 1977 SAVs are needed to replace 100,000 private vehicles. Similarly, Bischoff and Maciejewski (2016) concluded that 100,000 SAVs could replace 1.1 million private vehicles to serve 2.5 million trips on a typical weekday. The trip-to-vehicle ratio in this particular case thus reaches 25, which is higher than other studies. While some of the differences in results could come from the differences among the cities studied, differences in study design and modeled system functioning and user preferences could also play an important role. Thus, there is a need for more research that is able to apply a consistent methodology across different cities to better understand how outcomes are affected by city-level characteristics vs. service characteristics.

Different from fleet sizing, research on SAV parking is predominantly simulation-based. These studies utilize detailed simulation to model system dynamics and assess parking demand and distribution (Okeke, 2020; Kondor et al., 2020). For instance, Zhang et al. (2015) conducted simulation experiments to explore the parking demand of SAVs in a hypothetical city. Comparing to the parking

Table 1
Some representative studies on SAV in the literature.

Literature	Fleet management	Parking management	Empty meter analysis	Reservation time	Max waiting time	OD balance	Demand rate	Multi-city comparison
Fagnant et al. (2015)	✓	✗	✓	✗	✓	✓	✗	✗
Zhang et al. (2015)	✓	✓	✓	✗	✓	✓	✓	✗
Bischoff and Maciejewski (2016)	✓	✗	✓	✗	✓	✗	✗	✗
Boesch et al. (2016)	✓	✗	✗	✗	✓	✗	✓	✗
Okeke (2020)	✓	✓	✗	✗	✓	✗	✗	✗
Kumakoshi et al. (2021)	✗	✓	✓	✗	✓	✓	✗	✗
Narayanan et al. (2022)	✓	✓	✓	✓	✗	✗	✓	✗
Choi and Lee (2023)	✓	✓	✓	✗	✓	✗	✓	✗
This study	✓	✓	✓	✓	✓	✓	✓	✓

demand for private vehicles estimated from survey data and previous research, the authors claimed that 90 % of private vehicle parking spaces can be saved if private vehicles are fully replaced by SAVs. Samely assuming a complete replacement of private vehicles with SAVs, Kumakoshi et al. (2021) found a 94 % reduction in parking demand with the greatest decrease in residential areas and business districts. In addition to parking demand, some studies also examine the potential increase of VMT of SAVs, primarily due to the empty pickup and search trips (Kondor et al., 2020). For instance, Kumakoshi et al. (2021) found that the implementation of SAVs may increase VMT by 14.9 %, leading to a more congested traffic network. With a particular focus on the daily commute scenario, Kondor et al. (2018) argued that a 2 % increase in VMT is needed to compensate for a 50 % reduction in parking when private vehicles are replaced by SAVs. Liu et al. (2022b) compared the induced VMT under different service modes: car-sharing and ride-sharing. In car-sharing mode, a vehicle serves one trip at one time, while vehicles are allowed to serve multiple trips with similar OD simultaneously in ride-sharing. They found that car-sharing could increase VMT, while car-sharing and ride-sharing together could reduce VMT.

Although fleet sizing and parking are interdependent in an SAV system, few studies have explored the integrated design problem. One exception is Choi and Lee (2023), which jointly optimizes the parking density and fleet size using an analytical model with the objective of minimizing the operational cost. To simplify the model, it is assumed that vehicles park immediately after dropping off passengers. Specifically, two system configurations are studied: one with a homogeneous service and parking zone, and the other with a two-zone structure representing the urban and suburban areas, respectively. Compared to current statistics in Seoul, South Korea, the authors concluded that the launch of the SAV service can result in a more than 80 % reduction in vehicle number and a 90 % reduction in parking density in both configurations. Nevertheless, the quantitative trade-off between reducing parking spaces and inducing extra VMT, along with their impacts on the system efficiency, is still unknown. This is exactly one of the key research questions tackled in this study.

Several recent studies further expand the SAV and parking literature. Li et al. (2024) explored the potential for car-free cities using agent-based simulation of SAV and park-and-ride integration in Brussels, underscoring the complex interplay between pricing, travel demand, and system sustainability. Hu et al. (2024) developed an optimization framework for shared autonomous electric taxis considering capacity-constrained parking, revealing that coordinated vehicle routing and parking management can greatly improve operational efficiency and reduce energy consumption. These works, along with others (Fakhrmoosavi et al., 2024; Pimenta et al., 2025), demonstrate the growing academic focus on integrated approaches to SAV deployment, fleet management, and parking strategy. Another important work by Hunter et al. (2024) investigated curb allocation and pick-up/drop-off (PUDO) strategies for SAV fleets using agent-based simulation and real-world data from Austin, Texas. Their study provides valuable insights on how PUDO density, fare price, and curb management influence fleet operations. Notably, they show that for a given fare price and fleet size, PUDO spacing has a significant impact on ridership, vehicle-miles travelled, vehicle occupancy, and revenue, offering key guidance for municipal planners considering the allocation of urban curb space in the era of SAVs. Our study builds upon and complements Hunter et al. (2024) by conducting a cross-city comparative analysis that examines how diverse urban layouts and operational parameters jointly affect SAV fleet and parking requirements. Additionally, we advance the methodology by integrating enhanced demand modeling and network optimization to capture city-specific operational realities.

2.2. Influential factors of SAV fleet and parking

The SAV fleet size and parking spaces could be affected by a variety of factors. Among them, the service mode, such as solo versus shared rides, is one of the most extensively studied. Solo rides serve only one trip request at a time while shared rides group several requests with overlapping routes (Narayanan et al., 2020). Narayanan et al. (2022) modeled an SAV system with a mixture of solo and shared rides. One key finding, also expected, is that a higher vehicle capacity leads to a smaller fleet size and potentially less VMT. Similarly, Seo and Asakura (2021) optimized the fleet size for an SAV service with vehicle capacities of one, two, and five. As expected, the service with maximum vehicle capacity results in the minimum fleet size.

Travel demand is another key factor that significantly affects fleet size and parking (Huang et al., 2020; Gurumurthy and Kockelman, 2022). Levin (2017) set the fleet size as 50 % of demand and estimated the fleet utilization rate when all demand was satisfied. They found that this rate decreased as the demand size increased. Differently, Boesch et al. (2016) evaluated SAV system performance under various combinations of demand and supply. It was observed that to maintain a 95 % demand satisfaction, the ratio of vehicle number to demand decreases when the demand level first increases. Yet, as demand continues to grow, the ratio stabilizes and converges to around 25 %. On the other hand, Okeke (2020) and Zhang and Wang (2020) analyzed the impact of travel demand on the SAV parking demand and distribution. They both found that a higher travel demand in general leads to lower parking demand, though it induces more parking in specific locations, such as residential areas. All the above studies are conducted via agent-based simulations.

In contrast to service mode and demand level, other factors, such as trip reservation time, maximum waiting time, and parking strategies, have received less attention in the literature. Ma et al. (2017) designed a reservation-based SAV system and found that a higher vehicle utilization rate can be achieved with a longer reservation time. Chen et al. (2024) investigated the real-time dispatch problem in SAV systems with hybrid (immediate and reserved) trip requests and revealed that integrating pre-booked requests into vehicle dispatch management can greatly enhance the system efficiency. In Kondor et al. (2020), two parking behaviors are defined: long-term parking of idle vehicles without trip assignments, and short-term parking of dispatched vehicles waiting to pick up passengers. It is found that a larger parking demand is associated with a longer maximum passenger waiting time threshold. On the other hand, Zhang and Guhathakurta (2017) investigated the impact of different pricing schemes of parking on the parking distribution. Specifically, a shift of parking from the city center to the suburbs was observed when free parking was replaced by a charge based on the land price.

To sum up, although previous studies have examined various influential factors of fleet size and parking demand in an SAV system, few of them have explored their joint impacts and trade-offs. Another crucial factor, though overlooked in existing studies, is the OD distribution since it directly affects how SAVs travel between trips and where they park being idle. Last but not least, there is still a lack of comparative analyses across multiple cities to identify the general pattern of how these factors impact SAVs. This study is thus largely motivated by these research gaps.

3. Simulation framework

The simulation system is developed using C++ implemented on an Ubuntu 22.04.4 LTS platform. The temporal resolution of the simulation is one minute, which effectively captures the system dynamics. Each agent in the system represents a homogeneous AV and serves only a single request at a time. The road network is represented by a set of intersections and links and extracted from OpenStreetMap (Lu and Zhou, 2023). Vehicles travel on the road network with a time-varying speed updated every 15 minutes. These speeds are derived from historical taxi trips data. We partition the one month of data into 15-minute time-of-day windows. For each window, we take the mean of observed weekday speeds from the same clock-time window over that month. Randomness in the simulation is introduced through the demand generation process, particularly in specifying the departure time, origins and destinations for each trip. In the remainder of this section, we will present in detail three main modules in the simulation regarding demand generation (Section 3.1), trip dispatching (Section 3.2), and vehicle movements (Section 3.3).

3.1. Demand generation

As discussed in Section 2, both demand level and OD distribution could have substantial impacts on SAV operations and consequently, the system performance. Therefore, we design the demand generation module to take two primary inputs: (1) the market penetration of SAVs (π) that dictates how many trips are generated at each simulation step, and (2) the OD balance rate (γ) that adjusts the spatial distribution of trips based on the baseline demand profile. Specifically, we construct the trip origin distribution P_o from the historical data demand using a Gaussian Mixture Model (GMM), which can represent monocentric and polycentric urban structures in continuous space via multiple Gaussian components. Then, we sample the trip destination from the following distribution characterized by $\gamma \in [0, 1]$:

$$P_d(x, y) = \gamma P_o(x, y) + (1 - \gamma) P_u(x, y), \tag{1}$$

where (x, y) represents a point within the defined space, and P_u denotes a uniform distribution. By mixing P_o with a spatially neutral baseline P_u, Eq. (1) yields a simple but effective one-parameter family of destination distributions with an interpretable OD balance rate γ. The gap between origin and destination distributions shrinks as γ approaches 1. With Eq. (1), we can obtain the travel demand with different OD balances.

Although P_o and P_d define the marginal shares of departures and arrivals across the study area, these distributions do not specify how trips are distributed between locations. To preserve the spatial pattern of the actual demand, we divide the study area into 2 km × 2 km grids and formulate an optimization problem to construct the OD share matrix at the grid level:

$$\min_{P} \quad ||P - P^*||_2^2 = \sum_{i \in G} \sum_{j \in G} (p_{ij} - p_{ij}^*)^2 \tag{2a}$$

$$s.t. \quad \sum_{j \in G} p_{ij} = p_i^o, \quad \forall i \in G, \tag{2b}$$

$$\sum_{i \in G} p_{ij} = p_j^d, \quad \forall j \in G, \tag{2c}$$

$$\sum_{i \in G} \sum_{j \in G} p_{ij} = 1, \tag{2d}$$

$$0 \le p_{ij} \le 1, \quad \forall i, j \in G. \tag{2e}$$

The objective is to minimize the discrepancy between the generated matrix P and a reference matrix P^*, which is derived from the real trip data. G denotes the set of grids and p_{ij} is the share of trips from grid i to grid j. $P_o = (p_i^o)_{i \in G}$ and $P_d = (p_j^d)_{j \in G}$ are constrained to satisfy the origin and destination distributions P_o and P_d, respectively. The optimization model in Eq. (2) is convex (quadratic objective with linear equality constraints) and can be efficiently solved by commercial solvers, e.g., Gurobi. The resulting matrix P is scaled according to the total demand N during the simulation period and the market penetration π:

$$Q = (N \cdot \pi) \cdot P. \tag{3}$$

Then, we further disaggregate the OD demand flow Q to the intersection level. For each OD grid pair, we randomly sample origins and destinations within the corresponding grids to generate individual trips. Each trip is assigned a departure time based on the actual temporal pattern within the simulation period.

For each generated trip profile, another OD balance metric, denoted by B, is computed using realized trips at the grid level. Specifically, we calculate the ratio of inbound and outbound trips for grid i during each hourly interval as follows:

$$B_{i,h} = \frac{\min(N_{i,h}^{out}, N_{i,h}^{in})}{\max(N_{i,h}^{out}, N_{i,h}^{in})} \tag{4}$$

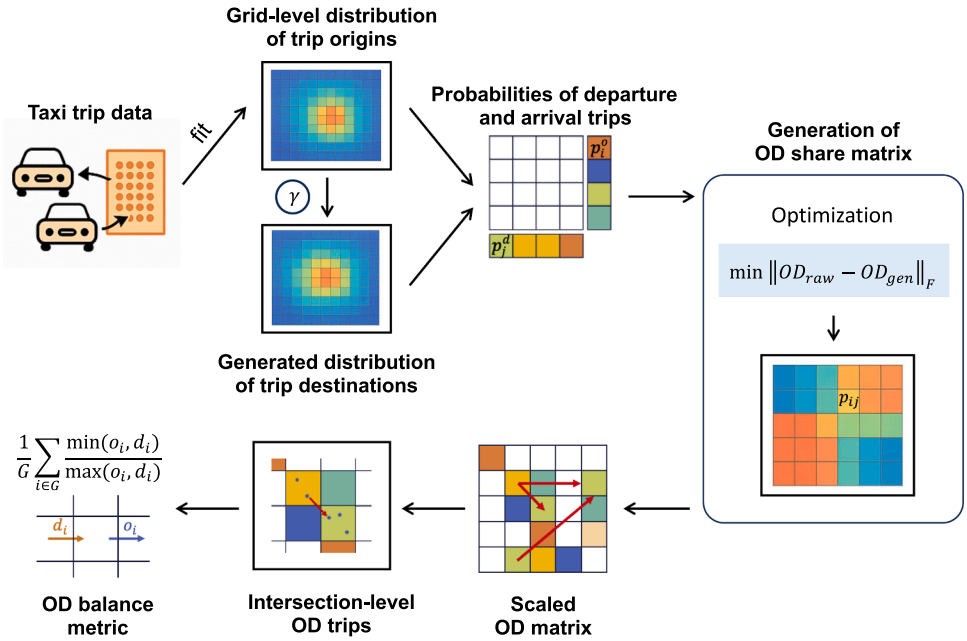

Fig. 1. Procedure of demand generation.

where $N_{i,h}^{in}$ and $N_{i,h}^{out}$ are respectively the number of in-bound and out-bound trips. The ratio $B_{i,h}$ then represents the OD balance in grid i during hour h, and the OD balance for hour h, denoted as B_h, is expressed as the average across all grids. Finally, the overall OD balance is calculated as

$$B = \frac{1}{N}\sum_h N_h B_h \tag{5}$$

in which N_h is the number of trips in hour h and $N = \sum_h N_h$ is the total trip number. The OD balance $B \in [0,1]$ and a larger value indicates a more balanced OD distribution. The procedure of demand generation is also illustrated in Fig. 1.

3.2. Trip dispatching

The SAV system in this study is reservation-based, requiring passengers to book their trips at least T_r minutes before their earliest departure times. On the other hand, we consider that passengers are willing to wait up to T_w minutes. The time step for the simulation is one minute. Hence, a departure time in the simulation system represents a one-minute window; for instance, trips departing between 10:00:00 and 10:00:59 are grouped into the 10:00 a.m. time step. The system dispatches trips at the beginning of each time step. Suppose that $T_w = 10$ min and $T_r = 5$ min. Then, at 10:00 a.m., the system can dispatch the trips with departing time at 10:04 a.m. and passengers would be picked up no later than 10:14 a.m. Mathematically, at time t, the system dispatches trips with departure times at $t + T_r - 1$ such that the passengers would be picked up no later than $t + T_r - 1 + T_w$. Vehicles that are currently parked, as well as those expected to complete orders between t and $t + T_r - 1$, are considered available for the trip dispatching at time t. Intuitively, T_r and T_w together expand the spatial range for vehicle searches, while T_r also determines the forward-looking time window for vehicle allocation. It is worth noting that when $T_r = 1$ min, the system operates as mobility on demand (MoD) in the framework.

The simulation implements batch-matching that groups unmatched orders and available vehicles at each time step. The objective is to minimize the total pickup distance under the maximum waiting time constraint, which sustains the service quality in the system. The mathematical formulation of the batch-matching problem is presented in (6) and the notations are summarized in Table 2.

$$\min_{a_{ij}} \quad \sum_{i\in V_r}\sum_{j\in V_d} a_{ij} d_{ij} \tag{6a}$$

$$s.t. \quad \sum_{i\in V_r} a_{ij} \le 1, \quad \forall j \in V_d, \tag{6b}$$

$$\sum_{j\in V_d} a_{ij} = 1, \quad \forall i \in V_r, \tag{6c}$$

$$d_{ij} = \begin{cases} \ell_{ij}, & \frac{\ell_{ij}}{s} + t_j \le t + T_r - 1 + T_w, \\ M & \frac{\ell_{ij}}{s} + t_j > t + T_r - 1 + T_w \quad or \quad j \in \tilde{V}_d, \end{cases} \tag{6d}$$

$$a_{ij} \in \{0,1\}, \quad \forall i \in V_r, j \in V_d. \tag{6e}$$

Table 2
Notations in the batch-matching problem.

Notation	Meaning
a_{ij}	Decision variables, i.e., $a_{ij} = 1$ if order i is matched to vehicle j, otherwise $a_{ij} = 0$
d_{ij}	Pickup distance of a match between order i and vehicle j
ℓ_{ij}	Distance between order i and vehicle j in the network
M	An arbitrarily large value to represent the pickup distance of an infeasible match
s	Vehicle travel speed in the road network
t	Current time step
t_j	Time when vehicle j is available
T_r	Reservation time
T_w	Maximum waiting time
V_r	Set of orders
V_d	Set of vehicles
$\tilde{V}_d$	Set of dummy vehicles

In the matching problem, Constraint (6b) states that each vehicle is at most matched to one order and Constraint (6c) requires all orders to be matched. Here, it implicitly assumes the number of vehicles is larger than the number of orders. When such a condition does not hold, we add a set of dummy vehicles, denoted by $\tilde{V}_d$, into the matching problem and specify the corresponding pickup distance to be an arbitrarily large value M as per Constraint (6d). For vehicles that cannot pick up the passenger within the time window $[t_j, t + T_r - 1 + T_w]$, where t_j is the earliest time vehicle j becomes available (e.g., time to drop off current passenger), the pickup distance is also assigned to be M. We solve the batch-matching at each time step using the Hungarian algorithm (Ahuja et al., 1993), which returns an optimal assignment in polynomial time and is fast at our problem scales.

It is worth noting that M indicates an upper-bound/maximum acceptable pickup distance to ensure the optimizer will always prefer any feasible vehicle-order pair over an infeasible one. Therefore, when a large penalty is added to each infeasible match, (6) also maximizes the number of matches. This result is formally stated and proved in Proposition 1. Accordingly, the SAV operator can balance the trade-off between total pickup distance and demand satisfaction by choosing the value of M.

Proposition 1. *When M is sufficiently large, the optimal solution to (6) not only minimizes the realized total pickup distance but also induces the maximum number of matches.*

Proof. Let $\boldsymbol{a}^*$ and $\overline{\boldsymbol{a}}$ be the optimal and any feasible solutions to (6), respectively. Given each solution, we can further specify a set of assigned orders O_a with pickup distance $d_{ij} = \ell_{ij}$ and a set of unassigned orders O_u with pickup distance $d_{ij} = M$.

Due to the optimality of $\boldsymbol{a}^*$, we have

$$\sum_{(i,j)\in O_a^*} d_{ij} + M|O_u^*| \le \sum_{(i,j)\in \overline{O}_a} d_{ij} + M|\overline{O}_u|, \tag{7}$$

$$\Rightarrow \sum_{(i,j)\in O_a^*} d_{ij} - \sum_{(i,j)\in \overline{O}_a} d_{ij} \le M(|\overline{O}_u| - |O_u^*|) \tag{8}$$

Therefore, when M is sufficiently large, the condition $|O_u^*| \le |\overline{O}_u|$ naturally induces Eq. (7). □

3.3. Vehicle movements

The road network contains highways, primary roads, secondary roads, and tertiary roads. Based on common urban transportation regulations, each type of road has specific operational restrictions, as summarized in Table 3. Following the restrictions, vehicle movements are classified into pickup trips, delivery trips, and parking trips. All these trips follow the shortest path in the road network.

If vehicles have not been assigned to subsequent orders upon completing an order, they will move to park, which corresponds to a parking trip. Vehicles first check the parking permission of the intersections within a 1 km radius. If such parking-allowed intersections exist within this range, vehicles search for available parking spaces at these locations. Otherwise, vehicles find the nearest parking-allowed intersections and search for available parking spaces. Similar to trip dispatching, the simulator performs a bi-partite match between idle vehicles and available parking spaces at each time step, with the objective of minimizing the total parking distance. If a vehicle cannot find a space to park, a new parking space will be generated at the nearest parking-allowed intersection. We measure

Table 3
Operational rules by road type in the simulation system.

Road type	Passenger pickup/drop-off	Vehicle park
Highway	✗	✗
Primary road	✓	✗
Secondary road	✓	✓
Tertiary road	✓	✓

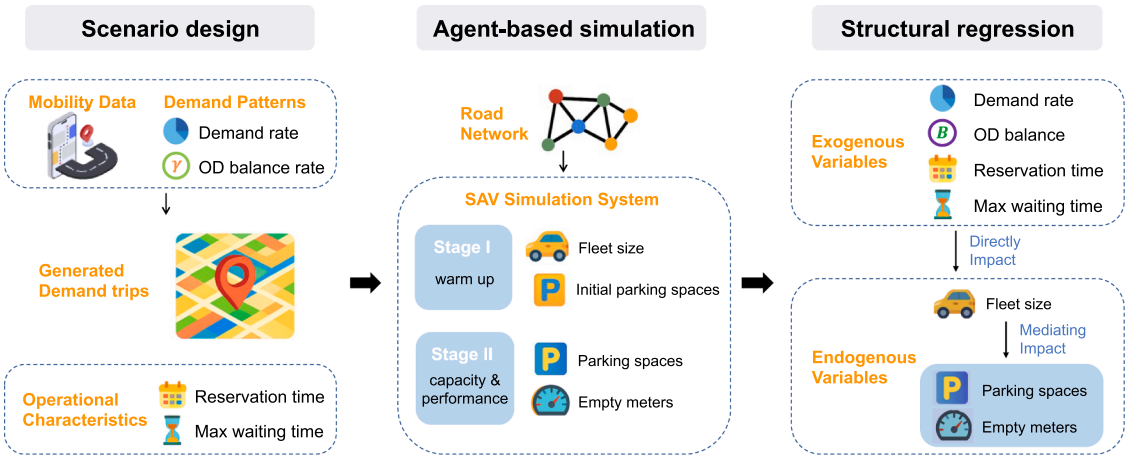

Fig. 2. Analytical framework and workflow.

the parking demand as the required number of parking spaces, i.e., the peak concurrent occupancy. At each intersection, we take the maximum number of parked vehicles at any time over the simulation period, and the citywide requirement at the same time is the sum of these intersection-level peaks.

4. Methodologies

Recall that the main objective of this study is to investigate the fleet and parking requirements for an SAV system and examine the impact of the operational characteristics and demand patterns on them. To this end, we first obtain the required fleet size and parking spaces under various simulation scenarios and then conduct structural regression analysis to investigate the direct and mediated effects of each factor. This research framework is illustrated in Fig. 2. In the following, we first introduce the design of simulation scenarios (Section 4.1), then describe the procedure of obtaining the fleet size and parking spaces for a particular SAV system, as well as the induced empty meters (Section 4.2), and finally present the regression model (Section 4.3).

4.1. Scenario design

The operation and performance of SAVs can be affected by various factors. In this study, we focus on the impact of operational characteristics and demand patterns. We investigate the role of operational characteristics by varying two main parameters in the simulation: reservation time (T_r) and maximum waiting time (T_w). The former describes how early passengers should send their trip requests before their desired departure times, and the latter gives the latest pickup time concerning the desired departure time. To capture broad operation scenarios, we set the reservation time to range from 1 to 30 minutes, which includes both on-demand and reservation-based scenarios. The maximum waiting time ranges from 0 to 20 minutes.

On the other hand, the demand pattern is summarized by average hourly demand rate ($\overline{N}_h$) over the simulation period and OD balance (B). Variation of these parameters corresponds to adjustments in the primary inputs, market penetration π and OD balance rate γ, for repeatedly generating sets of trips using the procedure described in Section 3.1. In this study, we consider the historical travel volume as the total demand and assume π varying from 0.1 to 1 with a step size of 0.1, while γ is set to vary from 0 to 1 with increments of 0.1.

4.2. Simulation procedure

We design a two-stage simulation procedure as shown in Fig. 2. The primary inputs are the road network with dynamic link travel times, the operational characteristics, and the generated demand profile based on the demand pattern for each simulation scenario. Stage I serves as a warm-up phase, aiming to obtain the required fleet size and the initial parking requirements to serve specific travel demand. The simulation starts with no vehicle and parking spot and does not reject any orders. Accordingly, the system dynamically introduces new vehicles and parking spaces as described in Section 3.3. The required fleet size is thus determined upon completing all orders and represents the vehicle supply requirement that would be able to serve all trips if sufficient advance knowledge of trips were available to the operator. This approach provides a comparable upper-bound on required fleet size and has been widely used in the literature (Kondor et al., 2020; Fagnant et al., 2015).

The fleet size and parking spaces derived in the first stage are then used in Stage II to further obtain the ideal parking spaces and evaluate the system performance. In this stage, the fleet size is strictly fixed and the vehicles are initially distributed at the location where they were introduced in Stage I. Extra parking spaces are allowed to be introduced to maintain the fleet size. The same demand profile is used whereas now orders may be rejected if no vehicle is available. The primary outputs of this stage are parking spaces,

empty meters and rejection rate. The parking spaces obtained in this stage serve as the final required parking spaces to support the fixed fleet size. The rejection rate reflects the reliability of the estimated fleet size. The two-stage simulation framework reflects a reasonable decision logic of operators for SAV deployment. Given the operational characteristics and demand patterns in a specific city, operators first determine the required fleet size. Then, the required parking spaces and induced empty meters are subsequently estimated.

4.3. Structural regression

To quantify the impact of operational and demand characteristics on the key efficiency indicators—fleet size, parking spaces and empty meters—in an SAV system, we conduct a regression analysis. In the system, these efficiency indicators are not independent but interrelated—for instance, a larger fleet may increase parking requirements. Thus, we employ an SEM approach that is capable of modeling this interconnected structure in our system. The general structural model can be expressed as

$$\eta = A\eta + \Gamma\xi + \zeta, \tag{9}$$

where η is a vector of endogenous variables, representing system internal outcomes. ξ is a vector of exogenous variables, representing external system inputs. A is a matrix of structural coefficients describing the effects among endogenous variables. Γ indicates the effects of exogenous variables on endogenous variables. ζ denotes the vector of error terms. In our system, the endogenous variables correspond to fleet size, parking spaces and empty meters, while the exogenous variables include reservation time, maximum waiting time, demand rate, and OD balance.

All variables are transformed using natural logarithm

$$\ln(\eta) = A\ln(\eta) + \Gamma\ln(\xi) + \zeta. \tag{10}$$

The logarithmic transformation serves several purposes. On the one hand, it linearizes potential nonlinear relationships. On the other hand, it reduces the difference in magnitude between variables, mitigating scale disparities and improving numerical stability in regression estimation. In Eq. (10), A represents elasticities among endogenous variables, that is, the percentage change in one efficiency indicator associated with a 1 % change in another indicator. Γ contains the elasticities of endogenous variables with respect to exogenous variables, quantifying the percentage change in one system efficiency indicator resulting from a 1 % change in an operational or demand factor.

5. Empirical study

5.1. Study area and datasets

The study area includes the central districts of three urban cities: Chengdu and Shanghai in China, and New York City (NYC) in the United States. These cities exhibit diverse structures and layouts:

- Chengdu is a monocentric city with a radial layout. The study area is within the Second Ring Road, as shown in Fig. 3A, which covers 120 square kilometers with 1510 intersections and 5822 road links. 1.8 % of intersections are distributed on highways, 36.7 % on primary roads, and 61.5 % on other roads. This area consists of a mixture of residential zones, commercial districts, and cultural landmarks, thus attracting a high density of daily travel activities.
- Shanghai features a polycentric structure, and the selected study area covers the primary and secondary centers with seven main districts, as shown in Fig. 3B. The region spans 302 square kilometers and contains 2440 intersections and 11,205 road links. The road network comprises 7.0 % of intersections on highways, 33 % on primary roads, and 60 % on other roads. A majority of commercial and residential activities in the city are concentrated within the region, leading to a high travel demand.
- Our analysis of NYC focuses on Manhattan. As shown in Fig. 3C, Manhattan has a rectangular shape spanning 59 square kilometers, and a dense road network with 2110 intersections and 7848 road links. The intersections are identified as 8.7 % on highways, 38.9 % on primary roads, and 52.4 % on other roads. As the financial and cultural center of the city, Manhattan features a high density of activities and consequently high travel demand.

Considering that taxi services reflect real-world ride-hailing mobility and SAVs operate similarly, we build the demand profile based on the historical taxi demand collected in the studied cities. Specifically, we used the taxi trip records over November 2016 in Chengdu, April 2015 in Shanghai, and February 2016 in Manhattan. Each trip record contains the origin and destination, as well as the departure and arrival times. From these trip records, we also compute the average road-network travel speed for each 15-minute time-of-day window by averaging weekday observations from the same window over the corresponding month, which serves as the time-varying speed in the simulation system. The GMM is fitted to historical origin locations via the expectation-maximization algorithm (implemented in a Python library scikit-learn); component means, covariance matrices, and mixture weights are estimated from data, while the number of components K (indicating the number of urban clustering centers) is guided by information-criterion profiles, i.e., Bayesian information criterion (BIC) and Akaike Information Criterion (AIC), and complemented by the kernel density estimation (KDE) maps. As can be seen in Appendix A (Figs. A.13–A.15), the number of components is 15, 17, and 18 for Chengdu, Shanghai, and Manhattan (NYC), respectively.

Fig. 4 plots the average trip number per hour on weekdays for each city. In Chengdu and Shanghai, three peaks can be identified in the morning, middle of the day, and evening, though the exact time intervals are different between the two cities: Chengdu has

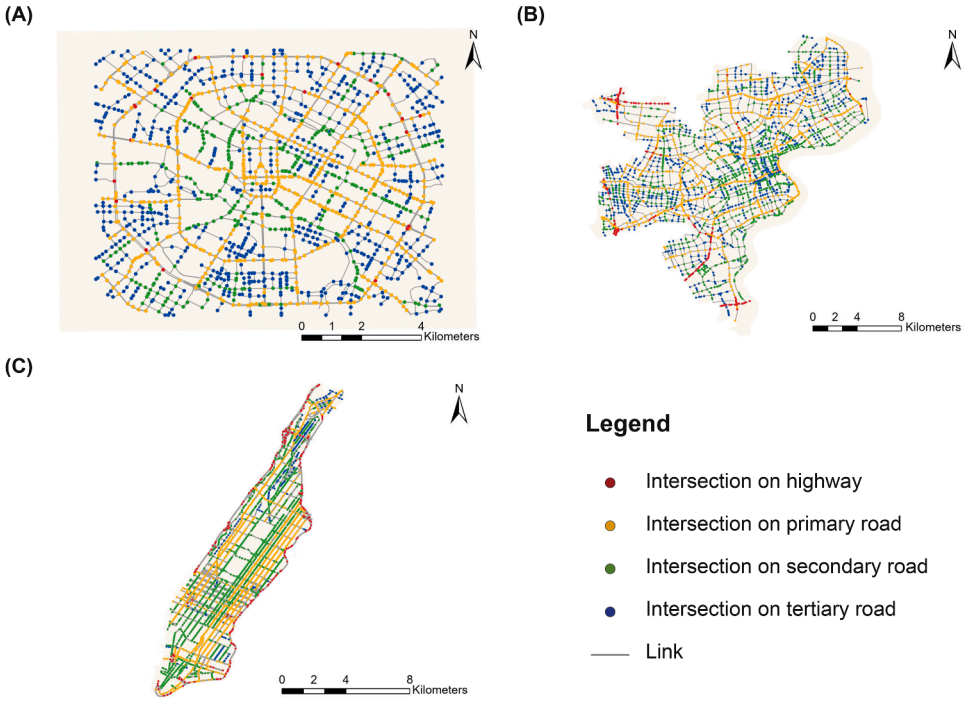

Fig. 3. Study area: (A) Chengdu, China; (B) Shanghai, China; (C) Manhattan of New York City, USA.

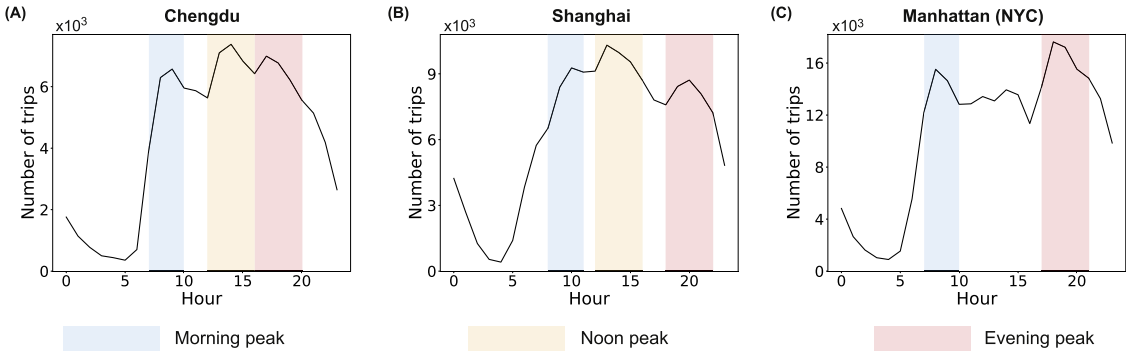

Fig. 4. Hourly demand in (A) Chengdu, (B) Shanghai, and (C) Manhattan (NYC).

Table 4
Average OD balance distribution during peak hours.

City	Morning peak	Noon peak	Evening peak
Chengdu	0.60	0.80	0.78
Shanghai	0.76	0.81	0.71
Manhattan (NYC)	0.58	-	0.54

relatively earlier morning and evening peaks from 7 AM to 10 AM and 4 PM to 8 PM, respectively, whereas, those in Shanghai are centered at 10 AM and 8 PM. Differently, Manhattan only shows clear morning and evening peaks: the former between 7 AM and 10 AM, and the latter between 5 PM and 9 PM.

Based on the identified peak periods, we proceed to compute the average OD balance in each city and peak, as reported in Table 4. In Chengdu, the OD pattern is the least balanced during the morning peak, when most travelers commute from the peripheral areas to the city center. The demand shows less imbalance during the other two peaks likely because the trip purposes are rather diverse. In contrast, Shanghai exhibits a similar and relatively high OD balance throughout the day, potentially because of the mixed land use. Finally, Manhattan shows a high OD imbalance in both morning and evening peaks, possibly due to the employment-residence separation, with concentrated business activity in Lower Manhattan and more residential areas in Upper Manhattan.

Table 5
Comparison of simulation efficiency in different cities.

City	No. of links	No. of intersections	Avg. trip volume	Avg. runtime (s)
Chengdu	5822	1510	25,759	124.0
Shanghai	11,205	2440	34,653	110.5
Manhattan (NYC)	7848	2110	56,451	563.0

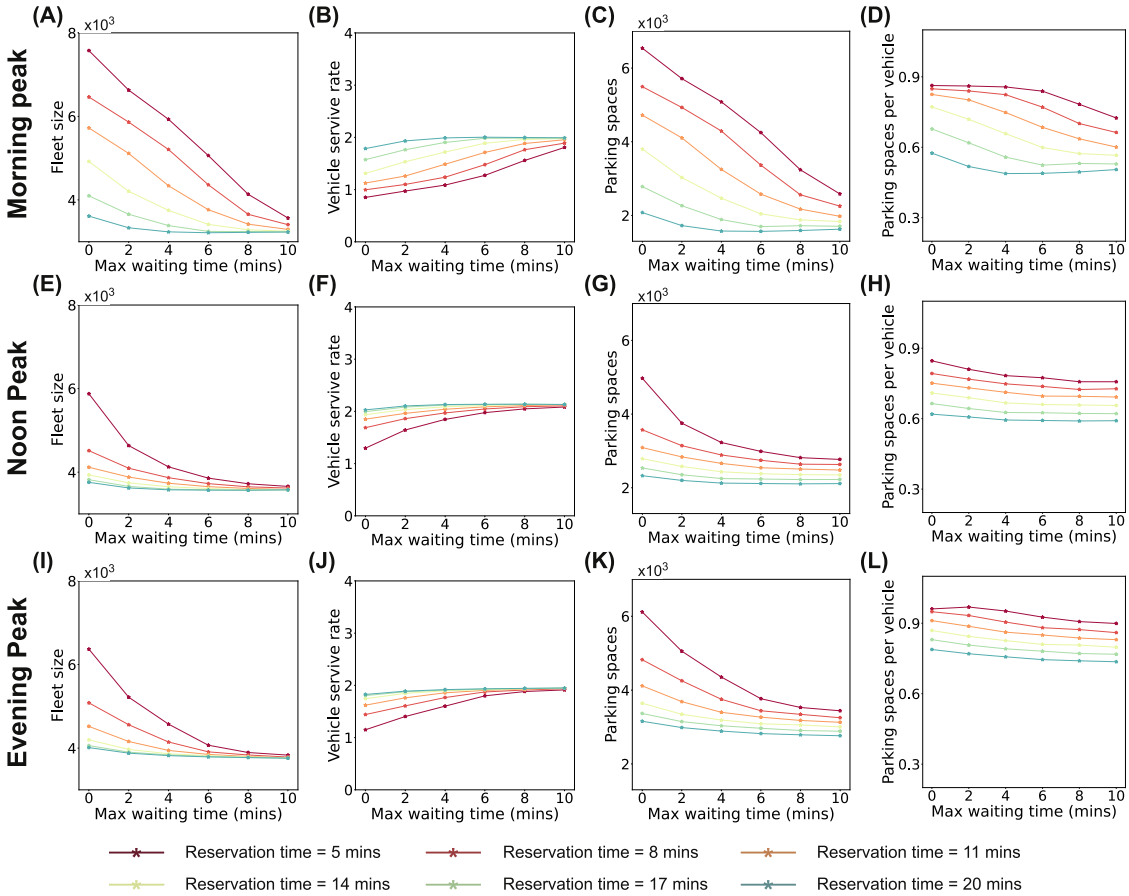

Fig. 5. SAV fleet and parking spaces in Chengdu, China.

5.2. SAV system design and performance under actual taxi demand

This section aims to uncover the required fleet size and parking spaces under current demand and relatively reasonable operational characteristics (i.e., reservation time and maximum waiting time). To demonstrate the simulation efficiency, we take the morning peak as an example and randomly select five weekdays' morning-peak periods for each city and run the simulations. As shown in Table 5, the average simulation times are 124.0 s, 110.5 s, and 563.0 s for Chengdu, Shanghai, and Manhattan, respectively. The simulation time in Manhattan is much longer than that in Chengdu and Shanghai because it has more demand with higher OD imbalance. The greater and imbalanced OD demand requires a larger fleet, resulting in a much longer calculation time in the batch-matching procedure and thus a much longer simulation time.

We further investigate the system performance regarding the empty meters and passenger rejection rate with each system design. As such, we directly use the original demand profile as the simulation input instead of generating it based on the method introduced in Section 3.1. Specifically, for each city, we randomly select five weekdays and extract the demand profile during each peak period. The reservation time is set from 5 to 20 min with a step of 3 min, while the maximum waiting time ranges from 0 to 10 min with a step of 2 min. We then run the simulation on each combination of peak-period demand and operational characteristics independently.

Fig. 5 illustrates the system design with respect to various operational characteristics in Chengdu. The results are all averaged over the simulations. Besides the fleet size and parking spaces, we plot the number of parking spaces needed per vehicle and the service rate (i.e., the number of trips accomplished by each vehicle per hour).

Several key findings can be generalized from the figure. First, the fleet size varies with both reservation time and maximum waiting time. Specifically, fleet size decreases as reservation time and maximum waiting time increase, and the variances are much larger at short reservation times or maximum waiting time. Beyond the effect of operational characteristics, the upper bound of the fleet size highly depends on the OD balance while the lower bound is closely related to the demand rate. Specifically, a larger fleet is needed when the demand is imbalanced and when the demand rate is high. Conversely, the service rate is higher when a longer reservation time and higher maximum waiting time threshold are applied. In Chengdu, the service rate is around 1 to 2.

The parking spaces follow a similar pattern as the fleet size, while the parking spaces converge more slowly than the fleet size. The number of parking spaces per vehicle tends to decrease with the increase of reservation time for a particular maximum waiting time setting. The impact of maximum waiting time is more complicated; for example, under the scenario setting in the morning peak with a reservation time of 20 minutes, the number of parking spaces per vehicle decreases when the maximum waiting time is less than 4 minutes, while it increases a bit when the maximum waiting time is greater than 4 minutes. However, the general trend decreases with the increase of maximum waiting time for a particular reservation time setting, ranging from 0.4 to 1.0. This ratio is lower than the values reported for conventional vehicles which lies between 3 and 4 (Chester et al., 2010; Shoup, 2021). The relatively low ratio observed in this study may be attributed to the centralized management of vehicles and high vehicle utilization in the SAV system.

Similarly, Fig. 6 and Fig. 7 illustrate the system design in Shanghai and Manhattan (NYC), respectively. The observed trends of fleet size and parking spaces in these two cities align closely with those in Chengdu. However, Shanghai and Manhattan achieve a higher service rate of up to 3 trips per vehicle per hour. This increased efficiency may be associated with the different demand characteristics, for example, a more balanced or denser demand.

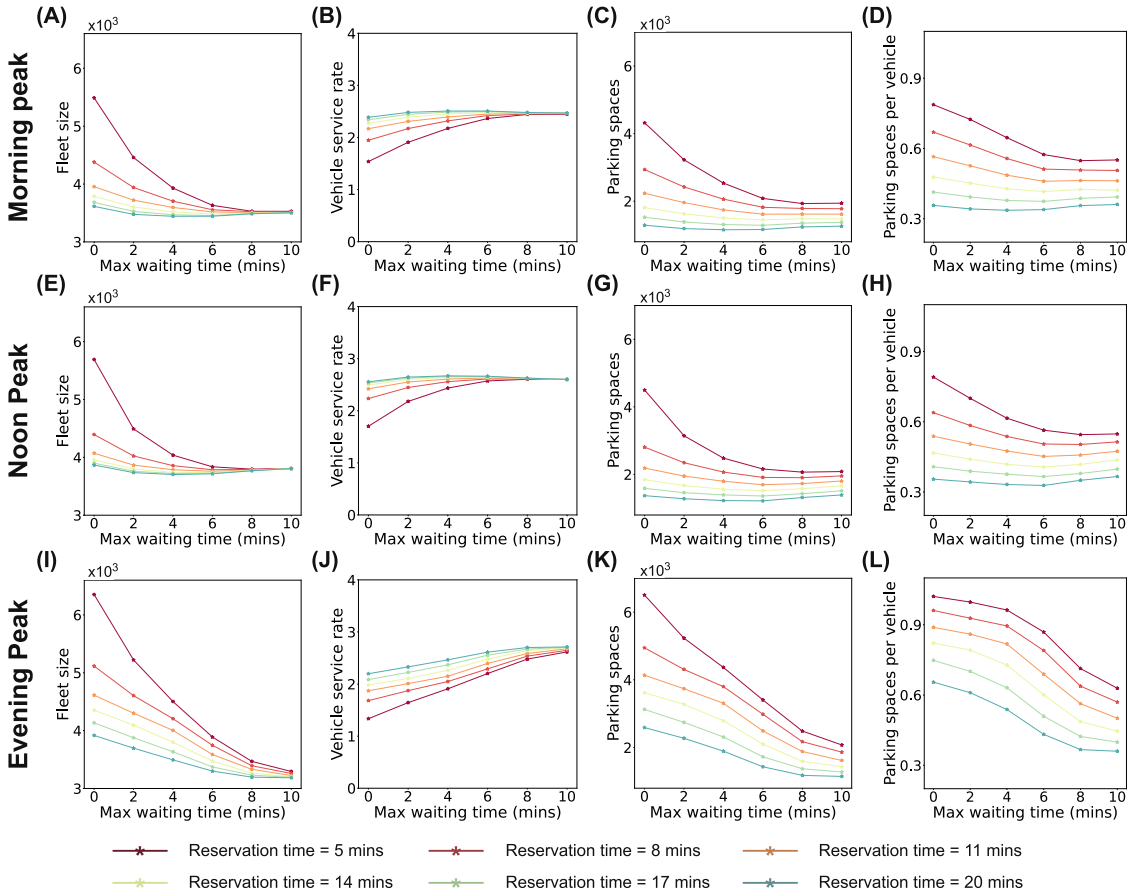

Fig. 6. SAV fleet and parking spaces in Shanghai, China.

The parking spaces per vehicle also range from 0.4 to 1.0 in Manhattan, while showing a wider range from 0.3 to 1.1 in Shanghai. This ratio appears to be influenced by city layouts and demand characteristics. Specifically, larger spatial extents and more imbalanced OD distribution result in a higher parking spaces ratio, possibly due to the sparser parking availability and increased vehicle idle time.

Fig. 8 illustrates the average empty meters and rejection rates under each system design in Chengdu. The evolution of empty meters exhibits a mixed pattern. Generally, empty meters increase with reservation and maximum waiting times. During the noon and evening peak, a decreasing trend is observed when reservation and maximum waiting times continuously increase. To further explore the reasons for the mixed pattern, we decompose the empty meters into pickup-related and parking-related distances. The two

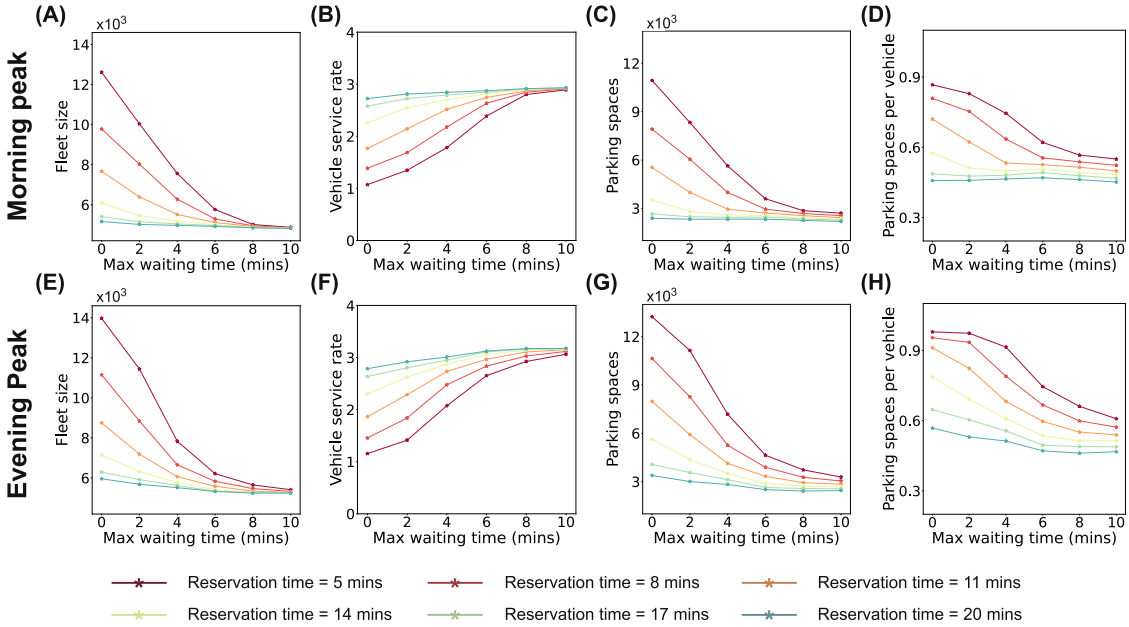

Fig. 7. SAV fleet and parking spaces in Manhattan (NYC), USA.

decompositions exhibit reverse trends as reservation time and maximum waiting time increase. Specifically, pickup-related distance initially rises as reservation and maximum waiting times increase, and then converges and even slightly decreases as these times are further extended, while the parking-related component consistently decreases.

The dynamics of pickup-related distance is tied to several reasons. On the one hand, extending the reservation and maximum waiting times relaxes the constraint on pickup distance. The flexibility allows vehicles to serve requests from farther locations. Thus, when this flexibility initially increases from a restrictive baseline, pickup distance rises because vehicles travel longer to capture distant passengers. On the other hand, the relaxed constraint enables the dispatcher to search for more optimal trip assignments within a broader spatial and temporal window. Then, once the reservation and maximum waiting times are sufficiently long, trip chaining becomes more efficient with shorter intervening distances, gradually reducing total pickup distance in the system. The OD balance is another critical factor affecting the dynamics. Imbalanced OD demand (e.g., demand in the morning peak) causes frequent long-distance vehicle relocation, especially when greater flexibility in time allows for broader spatial matching. As a result, longer reservations and maximum waiting times are required before the system benefits from efficient trip chaining to reduce pickup distance. In contrast, vehicles are already closer to orders under a balanced OD pattern. Modest flexibility could moderately increase pickup distance but allows the system to coordinate vehicle-order matches more effectively, thus reducing total empty meters.

The decrease in parking-related distance is mainly due to the decrease in fleet size. Recall that longer reservation time and maximum waiting time reduce fleet size and improve vehicle service rate. The results imply that vehicles spend more time picking up and delivering passengers instead of parking, thereby reducing idle repositioning for parking purposes. These findings suggest that the operational characteristics influence empty meters not only directly but also indirectly through the effects on fleet size. Furthermore, the rejection rate across all tested configurations is remarkably stable and remains below 0.05, suggesting that the SAV fleet is generally sufficient to accommodate the travel demand under the considered operational parameters and spatial patterns.

Similar trends of the empty meters and rejection rates are observed in Shanghai and Manhattan (NYC), as illustrated in Fig. 9 and Fig. 10. As the reservation and maximum waiting times increase, the empty meters increase and exhibit a mixed change pattern under a balanced OD distribution. The rejection rates are stable and stay below 0.05 across all scenarios. In addition, the upper and lower bounds of empty meters are more diverse across peak periods and cities. For instance, the empty meters during the morning peak in Chengdu are much higher than the noon and evening peaks, while in Shanghai and Manhattan, much higher maximum empty meters are observed during the evening peaks. The lower empty meters in Chengdu can be attributed to the lower demand, as well as the smaller operational area. For Manhattan, the much higher empty meters are likely driven by the high and dense demand, combined with the imbalanced OD.

The analysis of parking space distribution provides valuable insights into how SAVs interact with urban structures across different cities. Understanding the spatial patterns of parking demand under various conditions helps in optimizing parking allocation and improving system efficiency. Therefore, we further examine the simulated parking space distribution using an illustration example when reservation time is set to 5 minutes and maximum waiting time is 10 minutes, as shown in Fig. 11.

Chengdu, as a monocentric city, exhibits distinct parking space distribution patterns across different peak periods. In the morning peak, parking demand is highly concentrated in the central area, reflecting the influx of workers and shoppers traveling to the city center. This concentration aligns with Chengdu's urban layout, where a majority of commercial and employment hubs are situated in

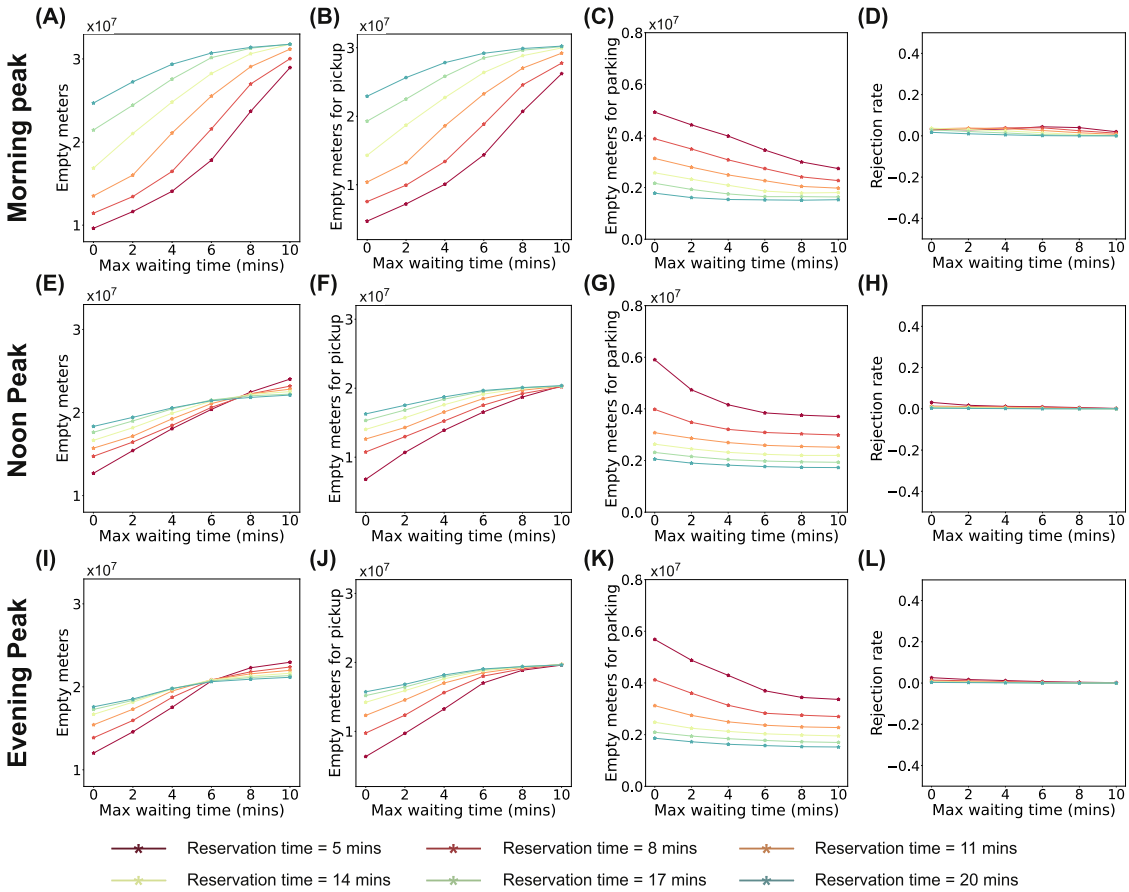

Fig. 8. SAV system performance in Chengdu, China.

the downtown core. As commuters reach their destinations, the demand for parking within the central district intensifies. During the noon peak, the demand for parking spaces becomes more evenly distributed, yet there are still visible clusters in the central areas. This shift suggests that while some employees remain near their workplaces for lunch, others return home or travel to peripheral areas for various activities. The dispersal of parking locations during this period indicates a diversified trip purpose beyond commuting. By the evening peak, parking demand spreads evenly across the city, with notable concentrations shifting towards the eastern districts. This pattern corresponds to commuters returning home from work, as well as individuals engaging in leisure activities outside the central district. Unlike the morning peak, the reduction in parking demand in the central area suggests a clear homeward migration of travelers. The results in Shanghai are similar to those in Chengdu. The parking space is concentrated in the central area during the morning, and then shifts from the center to the perimeter during the following peak periods.

Manhattan follows a high-density employment and entertainment-driven parking pattern, distinct from Chengdu and Shanghai. In the morning peak, parking demand is heavily concentrated in the middle and southern part of Manhattan, where major business districts such as the Flatiron, Financial District and Wall Street are located. This reflects the intense morning commute of workers arriving from outer boroughs and surrounding regions. By the evening peak, parking demand becomes more evenly distributed with a notable concentration emerging in the northern area. This shift away from Lower Manhattan reflects a transition from work-oriented trips to leisure and homeward travel.

5.3. Impact of operational characteristics and demand patterns

To further explore the influential factors of SAV system design and performance, we run simulations on broader scenarios with various operational characteristics and demand patterns during the bottleneck period, i.e., the peak period that potentially yields the maximum fleet size in Section 5.2. Specifically, we select the morning peak in Chengdu and the evening peak in Shanghai and Manhattan. With the ranges specified in Section 4.1, we randomly sample 1000 combinations of the four factors and then, for each of them, generate trips using the method of Section 3.1, run the simulation to estimate the four key operational metrics, and perform structural regression analyses across the 1000 cases on each city. Besides, a joint model is estimated over all three cities with the additional explanatory variable to capture the variation in service areas.

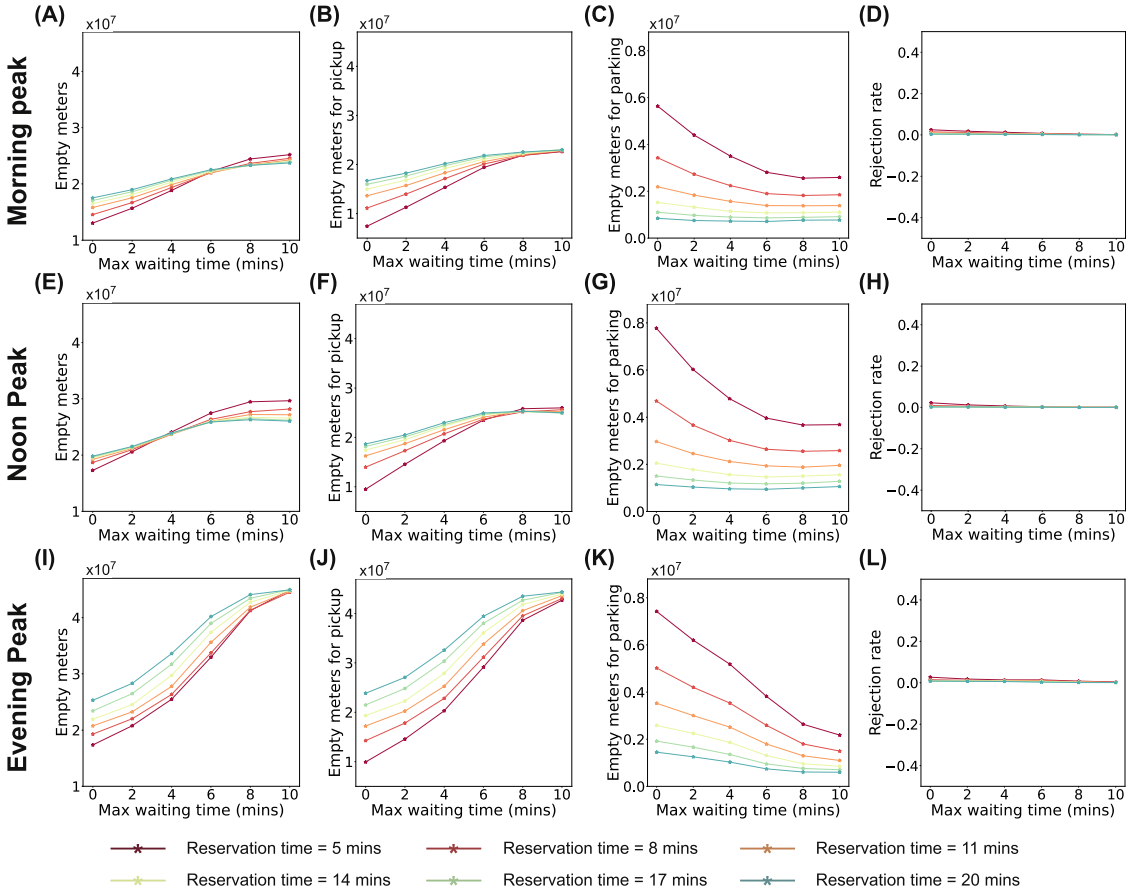

Fig. 9. SAV system performance in Shanghai, China.

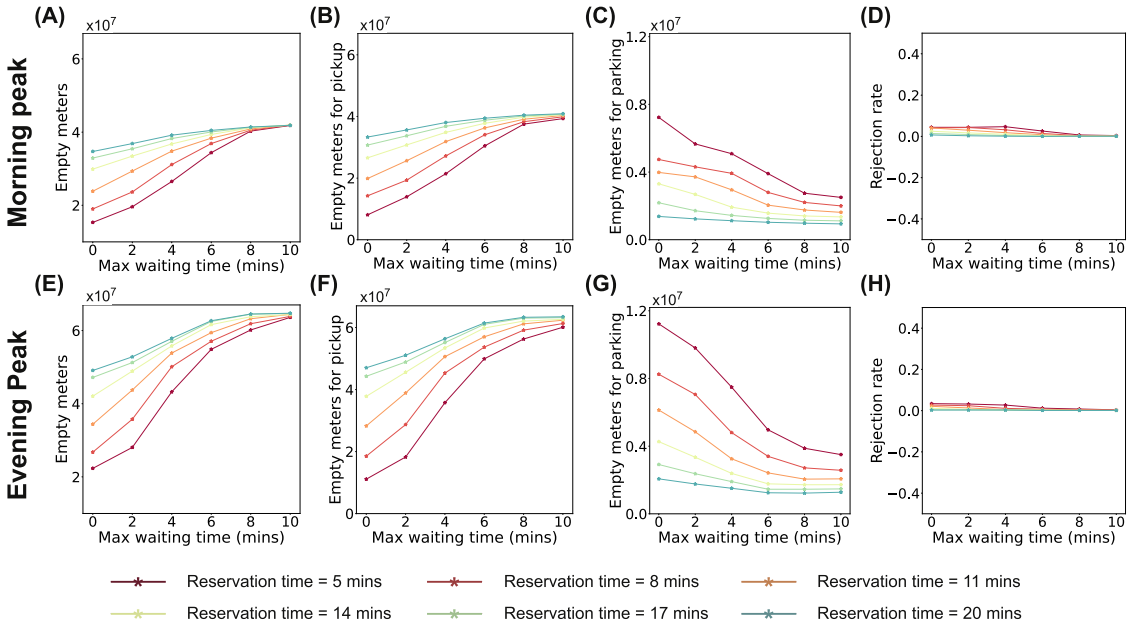

Fig. 10. SAV system performance in Manhattan (NYC), USA.

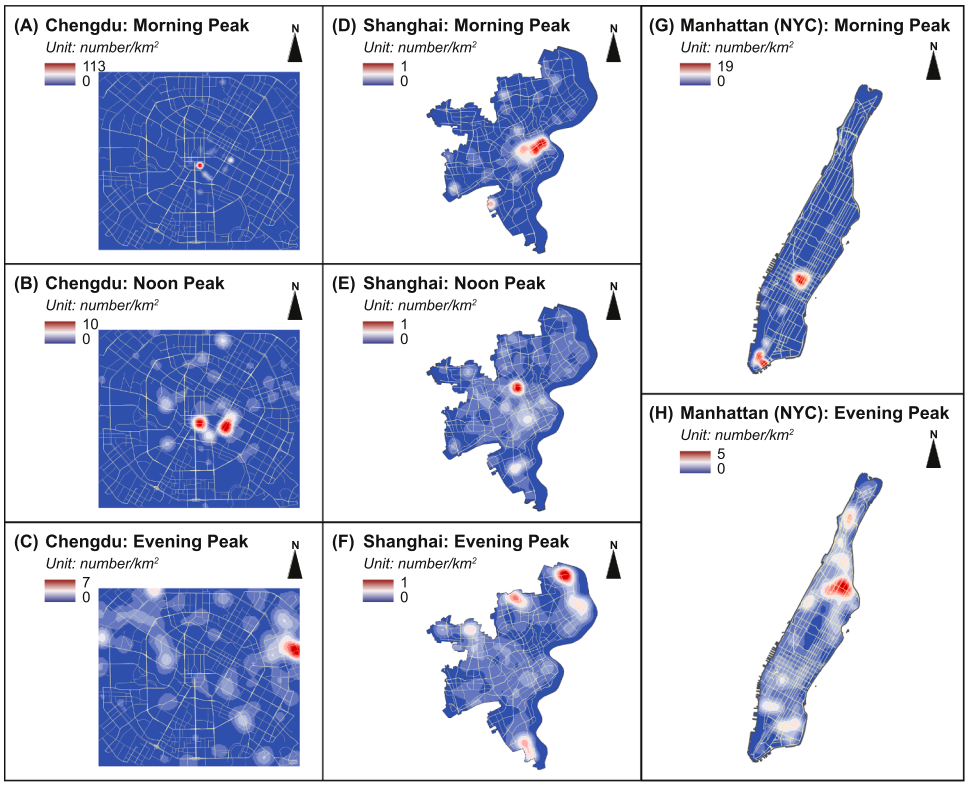

Fig. 11. Distribution of parking space demanded during peak hours in: (A-C) Chengdu, China, (D-F) Shanghai, China, and (G-H) Manhattan of NYC, USA.

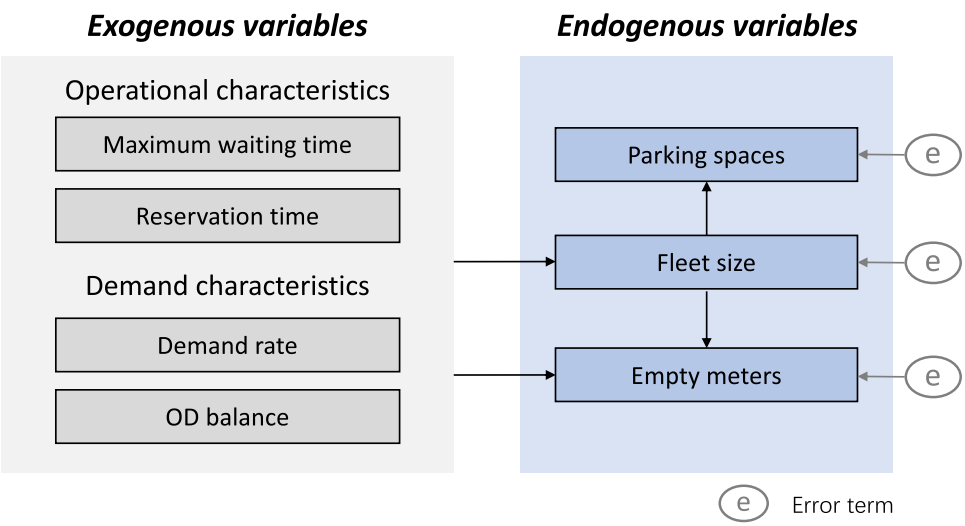

Fig. 12. Conceptual model of structural regression.

Fig. 12 illustrates the conceptual framework of the structural regression model, aligning with the logic of the simulation procedure. In Stage I, the fleet size is estimated with given operational and demand characteristics. Thus, these input characteristics directly affect fleet size. In Stage II, the same set of input characteristics and the estimated fleet size together affect the required parking spaces and induced empty meters. Upon preliminary analysis, we observe that the fleet size can largely explain the variance in parking spaces. Consequently, we omit the direct path from operational and demand characteristics to parking spaces to maintain model parsimony and theoretical coherence.

Table 6
Impact of operational and demand-side characteristics on SAV fleet and parking management.

City	Variables	Fleet size		Parking spaces		Empty meters	
		Direct effect	Total effect	Direct effect	Total effect	Direct effect	Total effect
Chengdu	**Model fit indices:** CFI = 0.98, TLI = 0.94, SRMR = 0.003						
	R^2	0.97		0.99		0.96	
	T_w	−0.05***	−0.05***	–	−0.05***	0.05**	0.15***
	T_r	−0.10***	−0.10***	–	−0.10***	−0.01*	0.20***
	$\overline{N}_h$	0.97***	0.97***	–	0.94***	2.95***	0.88***
	B	−1.12***	−1.12***	–	−1.09***	−4.14***	−1.74***
	Fleet size	–	–	0.98***	0.98***	−2.14***	−2.14***
Shanghai	**Model fit indices:** CFI = 0.95, TLI = 0.82, SRMR = 0.011						
	R^2	0.97		0.99		0.95	
	T_w	−0.07***	−0.07***	–	−0.06***	0.05**	0.21***
	T_r	−0.14***	−0.14***	–	−0.13***	0.12***	0.46***
	$\overline{N}_h$	0.96***	0.96***	–	0.92***	3.17***	0.81***
	B	−1.39***	−1.39***	–	−1.32***	−3.91***	−0.50***
	Fleet size	–	–	0.95***	0.95***	−2.45***	−2.45***
Manhattan (NYC)	**Model fit indices:** CFI = 0.99, TLI = 0.99, SRMR = 0.002						
	R^2	0.95		0.99		0.96	
	T_w	−0.08***	−0.08***	–	−0.08***	0.04**	0.23***
	T_r	−0.13***	−0.13***	–	−0.13***	0.17***	0.48***
	$\overline{N}_h$	0.96***	0.96***	–	0.96***	3.03***	0.78***
	B	−1.19***	−1.19***	–	−1.18***	−3.76***	−0.98***
	Fleet size	–	–	0.99***	0.99***	−2.34***	−2.34***
All cities	**Model fit indices:** CFI = 0.98, TLI = 0.93, SRMR = 0.014						
	R^2	0.96		0.99		0.86	
	T_w	−0.06***	−0.06***	–	−0.06***	0.11**	0.20***
	T_r	−0.13***	−0.13***	–	−0.12***	0.24***	0.42***
	$\overline{N}_h$	0.99***	0.99***	–	0.86***	2.35***	0.88***
	B	−1.52***	−1.52***	–	−1.50***	−3.44***	−1.20***
	Area	0.37***	0.37***	0.01***	0.37***	1.05***	1.05***
	Fleet size	–	–	0.98***	0.98***	−1.48***	−1.48***

Note: * significant at 0.1 level, ** significant at 0.05 level, and *** significant at 0.01 level.

Table 6 presents the regression results for Chengdu, Shanghai, Manhattan, and for the pooled dataset combining all three cities. The models fit the data reasonably well. The Comparative Fit Index (CFI) values remain above 0.9 and the Standardized Root Mean Squared Residual (SRMR) values below 0.08 among all models, indicating an acceptable fit between the hypothesized structure and the observed data (Rafiq et al., 2025). Tucker-Lewis Index (TLI) values are generally above 0.9, except for the model of Shanghai (TLI: 0.82), suggesting a slightly lower fit, likely due to greater demand heterogeneity in that city. Overall, the key indices suggest a satisfactory fit of our structural model.

As for the fleet size, the effects of operational and demand characteristics are significant and consistent in direction among cities. Specifically, extending reservation time and maximum waiting time reduces fleet size. This result is expected as longer reservation and maximum waiting times expand both spatial and temporal search range of vehicles, which essentially removes the matching friction between passengers and vehicles. The hourly demand rate is positively associated with fleet size as expected. A 1 % increase in demand rate leads to an almost 1 % increase in fleet size. In addition, a more balanced OD distribution is associated with a smaller fleet size, since balanced demand patterns allow more efficient vehicle circulation and reduce the need for idle repositioning. Specifically, 1 % improvement in OD balance reduces fleet size by more than 1 %. For parking spaces, fleet size exhibits strong explanatory power with estimated coefficients close to 1 across the three cities. Hence, operational and demand characteristics show a similar impact pattern on parking spaces.

The operational and demand characteristics influence empty meters directly and indirectly through fleet size. Regarding the direct effects, both reservation time and maximum waiting time as well as demand rate positively influence empty meters, while OD balance has a strong negative effect. Fleet size, as a key mediator in the indirect pathway, negatively affects empty meters. Specifically, a 1 % increase in fleet size results in a approximately 2 % decrease in empty meters. The negative effects of fleet size on empty meters may result from two key reasons. On the one hand, a larger fleet size results in denser vehicle supply across the network and less spatial mismatch between vehicles and orders, thereby lowering the total empty meters traveled. On the other hand, a larger fleet size allows for more efficient dispatch optimization, reducing deadheading trips and repositioning needs. The results also indicate that the reduction in vehicles and parking spaces comes at the cost of increased vehicle empty mileage.

The mediation of fleet size plays a crucial role in shaping the total effects of operational and demand characteristics on empty meters. For the reservation and maximum waiting times, the mediated effect of fleet size strengthens their direct positive effects on

empty meters. Longer reservation and maximum waiting times directly increase empty meters and reduce the required fleet size. The smaller fleet size in turn leads to more empty meters. Consequently, the positive direct and indirect paths reinforces the overall positive relationship. As a result, a 1 % increase in reservation time results in a 0.15 %-0.23 % increase in empty meters, while a 1 % increase in maximum waiting time raises empty meters by 0.20 %-0.48 %. In contrast, the mediation of fleet size weakens the impact of both demand rate and OD balance. Higher demand directly increases empty meters while induces a larger fleet, which indirectly reduces empty meters. A more balanced OD demand reduces empty meters while leads to a smaller fleet, which indirectly increases empty meters. For both variables, the indirect path partially offsets the direct effects, thus resulting in a weaker total effect. In total, a 1 % increase in demand rate raises empty meters by about 0.8 %, while a 1 % improvement in OD balance can offset this increase.

The direct and mediated effects of operational and demand characteristics are consistent in direction and magnitude across all cities, suggesting the effects are general and transferable across different urban settings. The consistency enables us to build the joint model with the combined data of the three cities. It is worth noting that we include the area as an exogenous variable in the joint model to control the cross-city heterogeneity resulting from the distinct urban scale. The estimated effects in the joint model remain stable and robust, further highlighting that the effects are not city-specific. Hence, the joint model can serve as a basic framework for system design and provide guidance for fleet and parking management across diverse urban contexts.

6. Policy implications

The findings of this study provide critical insights into the operations and demand-side factors influencing SAV performance. By analyzing real-world demand patterns and conducting a simulation-based evaluation of fleet size, parking spaces, empty vehicle travel, and service reliability (e.g., the reservation time and maximum waiting time), this study highlights the intricate dependencies between operational settings and SAV system efficiency. The results highlight the necessity of targeted policy interventions to ensure that SAV deployment aligns with broader goals of efficiency and sustainability, rather than merely serving as a substitute for conventional ride-hailing services. Here, we list some policy implications related to SAVs based on our study.

- **Strategic planning tool for SAV deployment.** The analytical framework proposed in this study offers valuable guidance for cities planning to deploy SAV system. Our findings reinforce the notion that SAV efficiency is highly context-dependent, meaning that a one-size-fits-all regulatory approach is unlikely to succeed in diverse contexts (Vosooghi et al., 2019; Karolemeas et al., 2024). According to our framework, cities can anticipate required fleet and parking spaces based on the urban structure, demand characteristics, and operational constraints, while maintaining an acceptable service rejection rate. Furthermore, our regression results reveal the general impact of operational and demand characteristics on SAV system design and performance across different cities. The finding presents an opportunity for planners to benchmark SAV performance against other cities in order to evaluate and adjust their own operations. The benchmarking process can encourage collaboration between cities, fostering knowledge exchange and the sharing of best practices.
- **Integrating SAV planning with land-use strategies.** One important finding of this study is the significant impact of demand characteristics on fleet size, parking spaces and induced empty meters. Specifically, a 1 % increase in demand rate raises fleet size, parking spaces, and empty meters by approximately 1 %, while a 1 % improvement of OD balance can offset the additional fleet and parking requirements and empty meters. Since urban structure fundamentally shapes OD distribution, the results highlight the importance of integrating SAV planning with adequate land-use and zoning strategies (Okeke, 2020). In cities with highly imbalanced OD distributions, zoning reforms, mixed-use development incentives, and job-housing balance policies should be introduced to balance the OD distribution. Additionally, demand-responsive pricing mechanisms–such as variable per-mile rates for SAV services based on congestion levels and OD balances–could be introduced to encourage more efficient spatial distribution of trips (Chen and Kockelman, 2016).
- **Balancing SAV deployment cost and environmental performance.** The negative impact of fleet size on empty meters suggests that the reduction in vehicle supply comes at the cost of increased empty meters (Zhang et al., 2015). A smaller fleet size reduces capital investment for AV deployment and parking infrastructure while leads to more emissions and energy consumption due to increased empty travel. The trade-off highlights the importance of designing system performance-based strategies rather than simply minimizing fleet size. Our findings show that reservation time and maximum waiting time lower fleet size but significantly raise empty meters through both direct and mediated pathways. To cut capital costs, operators may be incentivized to stretch these parameters, which increases empty travel of vehicles and subsequently leads to more energy consumptions and emissions. To avoid this outcome, regulators may carefully calibrate operational bounds linked to environmental performance, and require reporting of empty-kilometer intensity. Rather than rewarding the smallest fleet, cities should evaluate operators on a combined metric–empty kilometers per served trip or per passenger-km–ensuring that cost savings do not come at the expense of increased vehicle circulation and emissions. By embedding empty-travel performance into authorization and operating conditions, cities can guide SAV deployment toward both fiscal efficiency and environmental responsibility.
- **Managing trade-off between advance booking and Mobility on Demand (MoD).** Reservation time provides SAV system with forward-looking capacity of future demand, and thus allows more efficient trip dispatching and lowers fleet and parking requirements (Narayanan et al., 2022). For example, increasing reservation time by 1 % reduces fleet size and parking spaces by 0.10 %-0.14 %, roughly double the reduction achieved by a 1 % increase in maximum waiting time (0.05 %–0.08 %). Under cost-constrained deployment, encouraging advance booking allows operators to maintain a smaller and cost-effective fleet while keeping short waiting limits. However, long reservation windows reduce travel flexibility and disadvantage users with irregular schedules—such as gig workers, freelancers, and travelers with emergency. Operators could set reasonable upper bounds on

reservation windows to protect travel flexibility and accessibility. Another possible solution is to adopt hybrid designs that offer incentives for voluntary advance booking–such as guaranteed on-time pickup or modest price benefits–while maintaining an on-demand service baseline for spontaneous travelers (Cui et al., 2023).

7. Conclusion

In this study, we developed an agent-based simulation to study the fleet and parking management challenges associated with SAVs. Through a comprehensive two-stage simulation approach, we systematically evaluated how key operational characteristics (e.g., reservation time and waiting time) and demand-side factors (e.g., demand rate and OD balance) influence fleet size, required parking spaces, and overall system efficiency. Our analysis, grounded in real-world data from Chengdu, Shanghai, and Manhattan in NYC, revealed the underlying mechanisms by which these factors shape SAV operations across diverse urban contexts. The simulation results showed that SAV operations were highly sensitive to variations in demand rates, OD balance, reservation times, and maximum waiting times. Furthermore, our structural regression analysis revealed that the operational and demand-side variables significantly effect fleet and parking requirements as well as empty meters in SAV. The effects are consistent in direction and magnitude across different urban contexts, suggesting a potential generalization of these relationships. We also observe the mediating role of fleet size in transmitting the influence of operational and demand characteristics on parking demand and empty meters. In particular, a smaller fleet size helps reduce required parking spaces, while it leads to more empty meters. This finding highlights an inherent trade-off between minimizing fleet size and limiting empty travel of vehicles.

Our findings have significant implications for policymakers seeking to integrate SAVs into urban transport systems. The framework developed in this study can serve as a strategic planning tool, enabling cities to anticipate required fleet and parking capacities under different demand and operational scenarios and benchmark their performance against peer regions. Then, the strong effects of OD balance highlights that SAV deployment should be coordinated with land-use and zoning strategies that promote mixed-use development and job-housing balance to alleviate system pressure. Moreover, the trade-off between fleet size and empty travel suggests that relying solely on minimizing vehicle fleets may lead to unintended environmental burdens, underscoring the need to incorporate empty-kilometer performance metrics in SAV governance. Finally, the role of reservation time indicates that calibrated incentives for advance booking, coupled with guaranteed real-time service availability, can help cities capture efficiency gains while preserving flexibility and equitable access. Together, these insights offer a policy foundation for cities aiming to deploy SAVs in a manner that balances cost efficiency, environmental responsibility, and user experience.

While this study offers valuable insights for future planning and deployment of SAV systems through the analysis of real-world mobility data, several challenges remain. As autonomous vehicles become more widely adopted, the potential travel demand extracted from taxi data is expected to evolve into full-day, dynamic mobility patterns, where SAVs increasingly serve as viable substitutes for various transportation modes. Future research should explore other types of mobility datasets, such as mobile phone signaling data, to better capture the complex and evolving travel demand of potential SAV users. Incorporating such large-scale data would significantly increase computational complexity, presenting new challenges in efficient data processing and large-scale mobility modeling–a critical area for future exploration. Moreover, in short reservation and real-time settings, future requests are inherently uncertain and uneven across space and time. Leveraging historical demand profiles at the same time-of-day and day-of-week to proactively relocate idle vehicles is a promising direction to adapt to demand uncertainty. Short-term demand prediction combined with vehicle rebalancing can position vehicles ahead of anticipated peaks. Additionally, this study systematically analyzes key factors influencing SAV operations, providing a robust framework for understanding land use implications. Other factors, such as land-use and parking cost constraints, are worth further exploration, particularly regarding how parking demand and its spatial distribution are affected under these constraints. Future studies could delve deeper into these aspects, especially in dense urban environments where space availability poses significant challenges. Finally, the lack of real-world SAV data limits the empirical validation of simulation outcomes (Masello et al., 2022). Our system can serve as a reference to facilitate system comparisons and support validations across studies. In the long run, the public release of SAV data is crucial for calibrating models and enabling direct, empirical validation of simulation outcomes. Nevertheless, we believe this study serves as an important effort to support data-driven and evidence-based SAV planning. The agent-based simulation framework can be applied or extended to advance future research on autonomous mobility systems and their adoption in urban environments.

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

During the preparation of this work, the authors used GPT-4o in order to check the grammar and improve its clarity and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

CRediT authorship contribution statement

Yuqian Lin: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization; **Kenan Zhang:** Writing – review & editing, Supervision, Methodology, Formal analysis, Conceptualization; **Daniel Kondor:** Writing – review & editing, Methodology, Investigation, Conceptualization; **Zhan Zhao:** Writing – review & editing, Methodology, Investigation, Formal analysis, Conceptualization; **Carlo Ratti:** Writing – review & editing, Methodology,

Investigation, Conceptualization; **Yang Xu:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Data availability

The authors do not have permission to share data.

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Appendix A. Fitting origin distribution using Gaussian mixture model

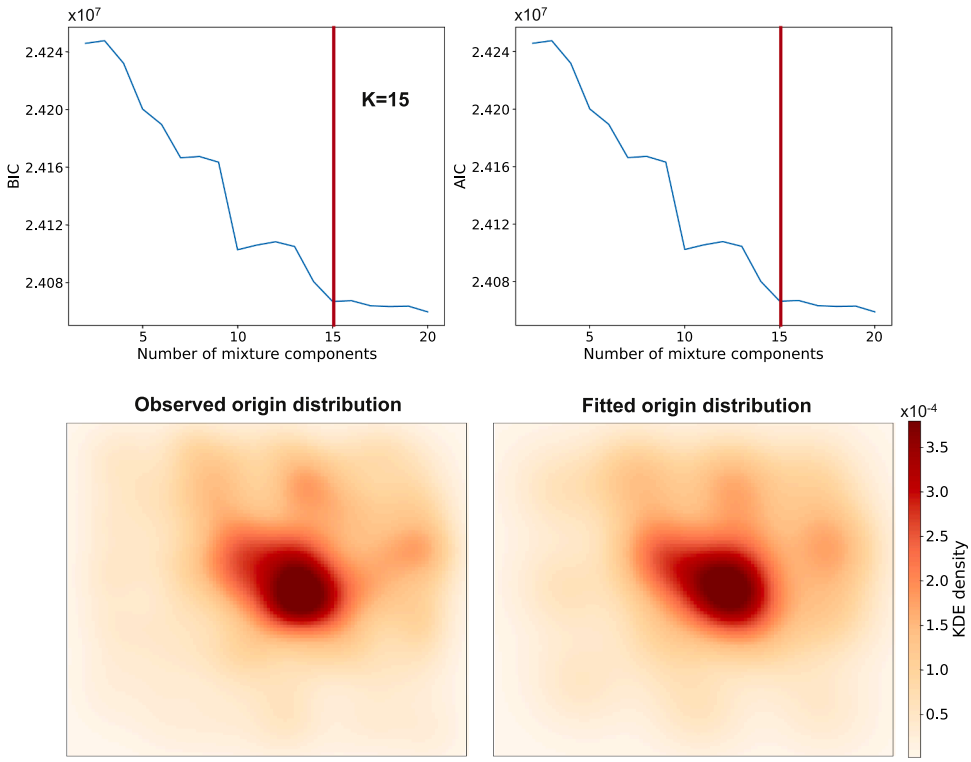

Fig. A.13. A comparison between the observed origin distribution and that fitted with the Gaussian Mixture Model during the morning peak in Chengdu, China.

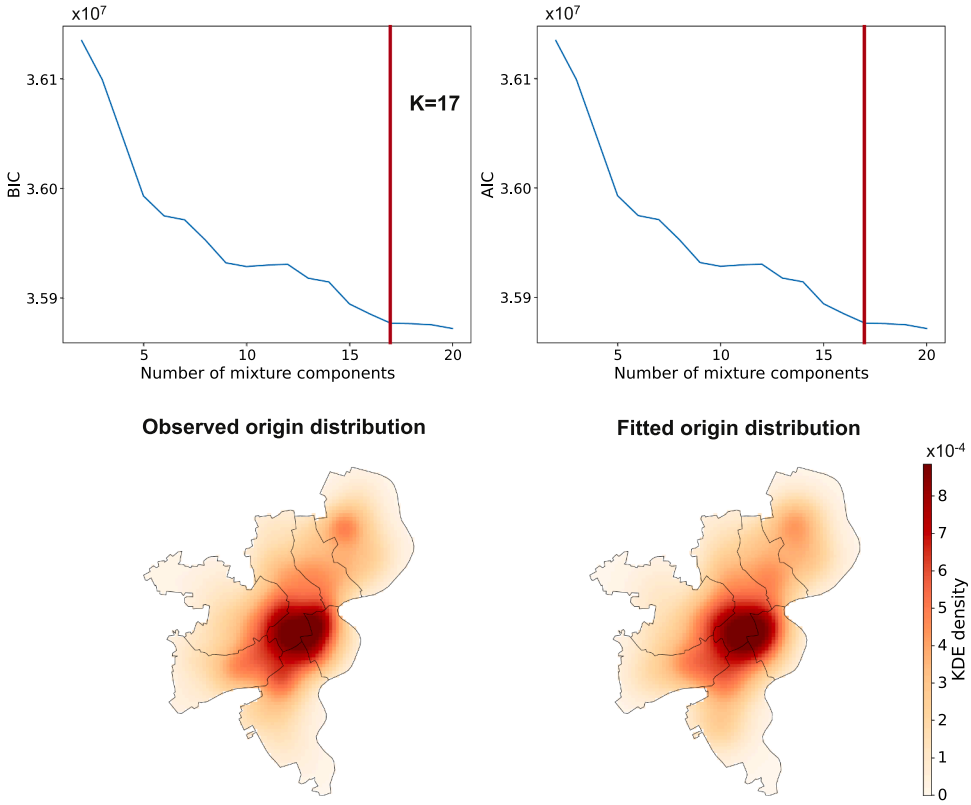

Fig. A.14. A comparison between the observed origin distribution and that fitted with the Gaussian Mixture Model during the evening peak in Shanghai, China.

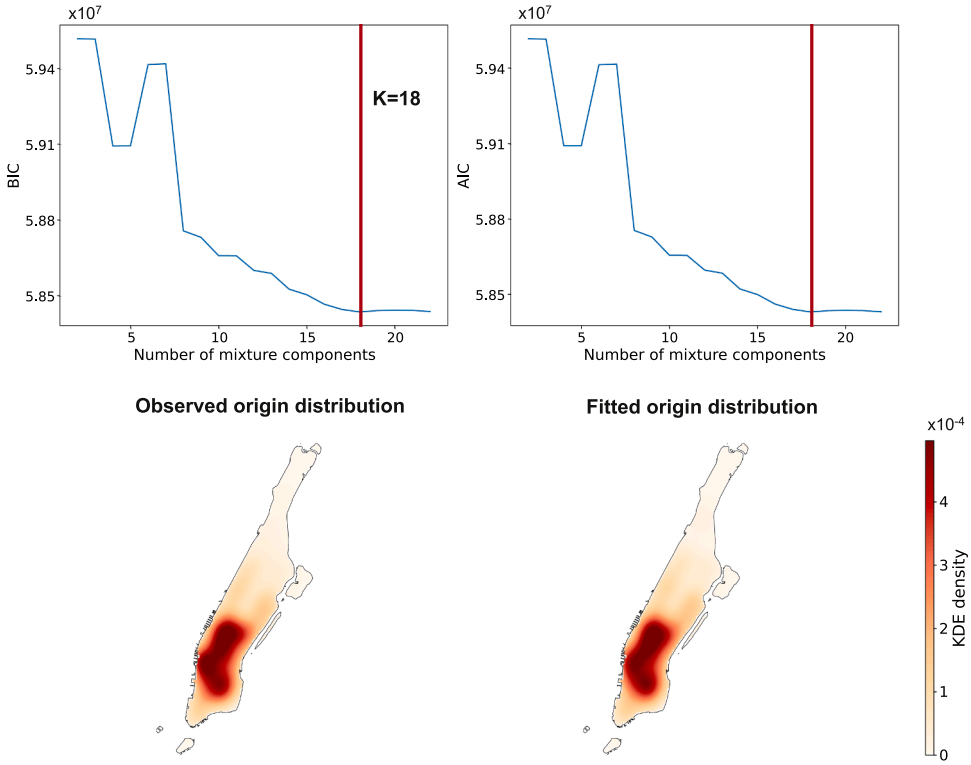

Fig. A.15. A comparison between the observed origin distribution and that fitted with the Gaussian Mixture Model during the evening peak in Manhattan (NYC), USA.

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