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RESEARCH ARTICLE

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Does e-hailing perform better than on-street searching? An investigation based on the temporal-spatial distributions of idle vehicles

Abstract This paper investigates whether e-hailing performs better than on-street searching for taxi services. By adopting the Poission point process to model the temporal-spatial distributions of idle vehicles, passengers' waiting time distributions of on-street searching and e-hailing are explicitly modeled, and closed-form results of their expected waiting time are given. It is proved that whether e-hailing performs better than on-street searching mainly depends on the density of idle vehicles within the matching area and the matching period. It is proved that given the advantage of e-hailing in rapidly pairing passengers and idle vehicles, the expected waiting time for on-street searching is always longer than that of e-hailing as long as the number of idle vehicles within a passenger's dominant temporal-spatial area is lower than $4/\pi$. Moreover, we extend our analysis to explore the market equilibria for both e-hailing and on-street searching, and present the equilibrium conditions for a taxi market operating under e-hailing versus on-street searching. With a special reciprocal passenger demand function, it is shown that the performance difference between e-hailing and on-street searching is mainly determined by the ratio of fleet size to maximum potential passenger demand. It suggests that e-hailing can achieve a higher capacity utilization rate of vehicles than on-street searching when vehicle density is relatively low. Furthermore, it is shown that an extended average trip duration improves the chance that e-hailing performs better than on-street searching. The optimal vehicle fleet sizes to maximize the total social welfare/profit are then analyzed, and the corresponding maximization problems are formulated.

Keywords taxi services, on-street searching, e-hailing service, passenger waiting time

1 Introduction

Taxis play a vital role in urban travel, especially for individuals without personal cars (e.g., Yang and Yang, 2011; Salanova et al., 2011). They provide a convenient and efficient door-to-door service that complements public transportation. Traditionally, some taxis gather at specific locations, such as train stations, airports, and hotels, while others rely on on-street searching to find passengers. However, on-street searching introduces uncertainty for both taxi drivers and passengers, impacting the expected waiting time, which is a crucial measure of service quality (Yang et al., 2010). This uncertainty can also affect passenger demand and trip fares due to the temporal-spatial imbalance of taxi service supply and demand (Yang and Wong, 1998). Fortunately, recent advancements in the internet and mobile technology have led to the emergence of on-demand ride-hailing services (Wang and Yang, 2019 for a review). These platforms connect idle vehicles with real-time passenger demand, significantly reducing waiting time uncertainties associated with traditional taxi services and addressing temporal-spatial disparities in taxi operations.

Given the advantages of on-demand ride-hailing services, it is widely believed that car-hailing platforms will significantly impact the market share of public transportation and traditional taxi services (e.g., Yu et al., 2020). Research has shown that approximately 33.1% of ride-hailing trips have the potential to replace public

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transportation (Kong et al., 2020), leading to an 8.9% decrease in public transport ridership (Diao et al., 2021). Moreover, the emergence of Uber has negatively affected the value of taxi licenses and the revenue of the taxi industry (Alley, 2016; Bond, 2015). In a study analyzing data from San Francisco in the spring of 2014, Rayle et al. (2014) concluded that travel app-based trips had replaced at least 50% of the traditional taxi market. Additionally, Cramer and Krueger (2016) demonstrated that car-hailing services exhibit a vehicle load rate that is 30%–50% higher than that of cruise taxis in terms of travel time and distance due to efficient matching technology. Further research by Schaller (2017) revealed that the total mileage of car-hailing trips in Manhattan in 2016 surpassed that of all traditional taxis. In Shenzhen, China, Nie (2017) analyzed data and revealed a significant decrease in taxi ridership due to competition from ride-sourcing. Tirachini and Gomez-Lobo (2020) used a survey to model the impact of ride-hailing applications on vehicle miles traveled in Santiago, Chile, and the results indicated an increase. Finally, Schaller (2021) examined data from Uber and Lyft between 2014 and 2020 and discovered that ride-hailing services lead to a doubling or greater increase in vehicle mileage in four major US cities and a suburban environment.

Considering in the popularity of car-hailing services, many scholars have conducted research on the positive effects of these services on the taxi industry. For instance, the emergence of e-hailing has allowed the taxi industry to attract new customers, particularly tech enthusiasts who may not be inclined toward traditional taxis (Vega-Gonzalo et al., 2023). Nie (2017) discovered that e-hailing services help increase the utilization rate of taxis. In addition, Harding et al. (2016) demonstrated that online car-hailing addresses issues such as credit commodities and a limited market within the taxi industry. Given the advantages of e-hailing, it is natural to question the extent to which it can enhance the efficiency of taxi services. In their study, He and Shen (2015) establish a spatial equilibrium model to analyze the relationship between pick-up and dispatch in cruise taxis and car-hailing and propose an equilibrium model that incorporates the elastic demand of taxi customers to illustrate the impact of ride-hailing apps on the taxi system. Zhang et al. (2019) adopted a queuing network approach to measuring the overall performance of various taxi services, while Daganzo and Ouyang (2019) developed a comprehensive modeling and analysis framework for different taxi services, including online car-hailing and cruise taxis. This framework allows for a comparison of urban transport modes in macroscenarios involving different types of cities and levels of demand.

However, there are scholars who argue that car-hailing is not always superior to traditional on-street searching. For example, Nie (2017) and Wang et al. (2020) both suggest that in areas with a relatively high concentration of unoccupied vehicles, ride-hailing is not necessarily more convenient than taxi cruising. In terms of short travel distances or low traffic speeds, Vignon et al. (2023) demonstrated that street-hailing may have a lower socially efficient cost than e-hailing. Furthermore, e-hailing addresses the challenge of uncertain travel time and location by matching the information of drivers and passengers, thereby enhancing the resilience (Shang et al., 2023) and sustainability of urban transportation systems (Shang and Lv, 2023; Shang et al., 2023).

Given the contentious views on the performance of e-hailing services, this paper aims to explore the potential improvement in the overall performance of the vehicle fleet, considering its temporal and spatial characteristics. In the context of on-street searching, both taxi drivers and passengers are unaware of each other's exact locations. This means that passengers must wait for an available taxi within a certain distance, while taxi drivers randomly search for passengers. On the other hand, e-hailing platforms have access to the locations of both idle taxis and waiting passengers. This allows them to quickly match a passenger with any nearby available vehicle. By employing a matching strategy such as pairing passengers with the closest idle vehicle, a passenger's waiting time depends on the estimated travel time of the matched taxi, which is determined by the vehicle's location (random) and prevailing traffic conditions. Therefore, analyzing the expected time of an idle taxi occurring within a certain distance and the anticipated travel time of the matched taxi can help model the differing performances of on-street searching and e-hailing, assuming the same random temporal-spatial distributions of idle vehicles.

Generally, two types of matching approaches are used in modeling ride-sourcing service markets (Li et al., 2021): inductive and deductive methods. The former emphasizes matching functions without investigating the detailed modeling of the micromatching processes. For instance, one widely adopted inductive approach is the use of the Cobb–Douglas production function (e.g., Zha et al., 2016; Wigand et al., 2020; Wang et al., 2020). In contrast, the latter focuses on the physical matching process between waiting customers and nearby idle vehicles. It derives specific matching functions based on proposed matching mechanisms, as seen in Xu et al. (2017) and Yang et al. (2020). There is also extensive research that employs queuing models to approximate customer waiting time in the ride-sourcing market (e.g., Taylor 2018; Bai et al., 2019). For a comprehensive review of these two types of matching approaches, please refer to Li et al. (2021). In this study, we employ the deductive method and utilize the Poisson point process to model the spatiotemporal distributions of idle vehicles. This approach allows us to explicitly model and deduce the passenger waiting time distributions for both on-street searching and e-hailing services. We provide closed-form results for the expected passenger waiting time for each service type, enabling a direct comparison of their performance in terms of waiting time.

Furthermore, we investigate the market equilibria for both e-hailing and on-street searching services. By defining an elastic demand function, we determine the equilibrium passenger demand and the number of idle taxis, facilitating a comparison of capacity utilization rates between the two service types. Specifically, we present closed-form results and a sufficient and necessary condition for e-hailing to achieve a higher equilibrium capacity utilization rate than on-street searching based on a special reciprocal passenger demand function. Additionally, we formulate maximization problems to determine the optimum number of vehicles for profit or social welfare maximization. We provide closed-form solutions for profit maximization, including the resulting passenger demand, for the aforementioned reciprocal passenger demand function. The main findings of this study are as follows:

• For the same arrival rate of idle vehicles, e-hailing services outperform on-street searching in terms of passenger waiting time when the supply is low. However, on-street searching may perform better when the supply is relatively high.

• For the same vehicle fleet size and elastic demand, the performance difference between e-hailing and on-street searching is primarily influenced by the ratio of the fleet size to the maximum potential passenger demand.

• E-hailing performs better than on-street searching when the ratio is low, and vice versa.

• Extending the average trip duration can increase the likelihood of e-hailing services outperforming on-street searching in terms of the expected waiting time.

The rest of this paper is organized as follows: Section 2 investigates the waiting time distributions of e-hailing and on-street searching. Section 3 analyzes the market equilibria and optimum vehicle numbers. Section 4 presents the numerical analyses, and Section 5 concludes the paper.

2 Waiting time distributions of e-hailing and on-street searching

In this section, we explore the waiting time distributions for passengers using e-hailing and on-street searching, assuming a given arrival rate of idle vehicles. Section 2.1 provides the assumptions and notations used in this study. Section 2.2 examines the passenger waiting time distribution for e-hailing, while Section 2.3 presents the passenger waiting time distribution for on-street searching.

2.1 Assumptions and notations

This section provides an overview of the notation and key assumptions utilized in this research. The notation is presented in Table 1, while the primary assumptions are outlined below.

A1. Traffic congestion is disregarded, and a constant traffic speed is assumed. Additionally, the average travel time within the vehicle is assumed to be consistent for all passengers.

A2. The size of the vehicle fleet is predetermined, while the passenger demand is elastic and inversely related to the generalized travel cost.

A3. Idle vehicles follow homogeneous spatial and temporal Poisson point processes (refer to Fig. 1[1)]). We do not consider the guidance provided by ride-sourcing platforms for repositioning empty vehicles. Consequently, the probability of k idle vehicles existing within a matching area of s per unit of time is given by (Chiu et al., 2013)

$$P_d\{k\} = \frac{\exp(-sN^i/S)(sN^i/S)^k}{k!}, \quad k = 0, 1, \ldots, N^i, \quad (1)$$

and the probability of the existence of k idle vehicles within a time period of Δt is given by

$$P_t\{k\} = \frac{\exp(-N^i\Delta t)(N^i\Delta t)^k}{k!}, \quad k = 0, 1, \ldots, N^i, \quad (2)$$

where S denotes the area of the road network.

2.2 Waiting time distribution of e-hailing services

For e-hailing services, it is assumed that the ride-hailing platform always matches a passenger with the nearest idle vehicle that arrives within a short matching period, Δt_{eh}, subsequent to the passenger's service request. For a passenger requesting service at a specific time and location, the expected total number of idle vehicles arriving within their matching period is calculated as:

$$N_t = \sum_{k=0}^{N} k\frac{\exp(-N^i\Delta t_{\mathrm{eh}})(N^i\Delta t_{\mathrm{eh}})^k}{k!} = N^i\Delta t_{\mathrm{eh}}. \quad (3)$$

Then, the probability of the existence of k idle vehicles within a matching area of s and within the matching period is given by

$$P_d^{\mathrm{eh}}\{k\} = \frac{\exp(-sN_t/S)(sN_t/S)^k}{k!}, \quad k = 0, 1, \ldots, N_t. \quad (4)$$

Considering the matching area of a disc with $s = \pi x^2$, where x denotes the radius of the matching area. Then, the cumulative distribution of the shortest pick-up distance, X, is given by

$$H_d^{\mathrm{eh}}(x) = 1 - P_d\{0\} = 1 - \exp(-\pi x^2 N_t/S), \quad x \geqslant 0. \quad (5)$$

1) Poisson point process is often used in stochastic modeling to describe locations of randomly distributed points in space (e.g., Arnott, 1996; Xu et al., 2017; Shen and Ouyang, 2023 for its application in the taxi/ride-sourcing markets)

Table 1 Notations used in this paper

Variable	Definition
N^i	Arrival rate of idle vehicles per unit time (one hour)
N	Vehicle fleet size
q	Passenger demand
T_0	Average trip time
w	Average waiting time of passengers
k	Number of idle vehicles $k = 0, 1, \ldots, N^i$
S	Area of the road network
Δt_{eh}	Matching period for e-hailing services
x_{eh}	Matching distance for e-hailing services
$\pi(x_{\text{eh}})^2$	Matching area for e-hailing services
X	Cumulative distribution of the shortest pick-up distance of e-hailing services
s	Matching area for e-hailing services
N_t	Expected total number of idle vehicles arriving within the e-hailing matching period
$P_d^{\text{eh}}\{k\}$	Probability of idle vehicles in a matching area and matching period for e-hailing services
$H_d^{\text{eh}}(x)$	Cumulative distribution of the shortest pick-up distance for e-hailing services
$F_W^{\text{eh}}(w)$	Cumulative distribution of passengers' pick-up time for e-hailing services
$f_W^{\text{eh}}(w)$	Density function of passengers' pick-up time for e-hailing services
$\overline{w}_{\text{eh}}$	Passenger's expected waiting time for e-hailing services
Δt_{os}	Matching period of on-street searching services
x_{os}	Matching radius of on-street searching services
s_{os}	Matching area for on-street searching services
N_s	Expected total number of idle vehicles arriving within the on-street searching matching area
$P_t^{\text{os}}\{k\}$	Probability of idle vehicles in a matching area and matching period for on-street searching services
$F_W^{\text{os}}(w)$	Cumulative distribution of passengers' pick-up time for on-street searching services
$\overline{w}_{\text{os}}$	Passenger's expected waiting time for on-street searching services
Δw	Difference in the expected waiting time between on-street searching services and e-hailing services
T_{w}	Walking time for taxi services
p	Trip fare
u_{eh}	Generalized trip costs with e-hailing services
u_{os}	Generalized trip costs with on-street searching services
β_0	Value of walking time
β_1	Value of waiting time
α	Value of trip time
$g(\cdot)$	Passenger demand function, which decreases with passengers' generalized trip cost
q_{eh}	Passenger demands of e-hailing services
q_{os}	Passenger demands of on-street searching services
N_{eh}^i	Equilibrium idle vehicle numbers for e-hailing services
N_{os}^i	Equilibrium idle vehicle numbers for on-street searching services
Q	Maximum passenger demand
γ	A parameter reflecting the sensitivity of demand on trip cost
c	Unit cost of one vehicle
N_{eh}^*	Optimal vehicle fleet size for e-hailing services under profit maximization
N_{os}^*	Optimal vehicle fleet size for on-street searching services under profit maximization
q_{eh}^*	Passenger demands for e-hailing services under profit maximization
q_{os}^*	Passenger demands for on-street searching services under profit maximization.

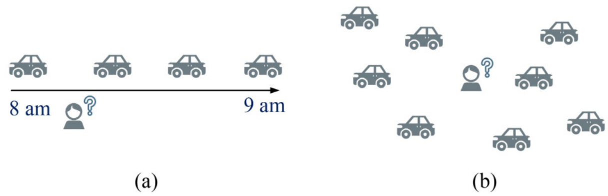

Fig. 1 The temporal and spatial arrivals of passengers: (a) Temporally dimensional arrivals; (b) Spatially dimensional arrivals.

Assuming that the waiting time is equal to the closest pick-up distance divided by a constant traffic speed, $W = X/v$. Then, we have the cumulative distribution and density function of passengers' pick-up time:

$$F_W^{\mathrm{eh}}(w) = 1 - \exp\left(-\pi(vw)^2 N_t/S\right), \quad w \geqslant 0, \tag{6}$$

$$f_W^{\mathrm{eh}}(w) = 2\pi v^2 w N_t/S \exp\left(-\pi(vw)^2 N_t/S\right), \quad w \geqslant 0. \tag{7}$$

From Eqs. (6)–(7), the passenger's expected waiting time with e-hailing is given by

$$\overline{w}_{\mathrm{eh}} = \Delta t_{\mathrm{eh}} + \frac{1}{2v}\sqrt{S/(N^i \Delta t_{\mathrm{eh}})}, \tag{8}$$

which depends on the matching time, the number of idle vehicles per unit space, and the traffic speed. By taking the derivative of Eq. (8) with respect to Δt_{eh}, we have

$$\frac{\partial \overline{w}_{\mathrm{eh}}}{\partial \Delta t_{\mathrm{eh}}} = 1 - \frac{1}{4v\Delta t_{\mathrm{eh}}}\sqrt{S/(N^i \Delta t_{\mathrm{eh}})}. \tag{9}$$

By setting Eq. (9) larger than 1, we have

$$\frac{16}{\pi}\Delta t_{\mathrm{eh}} N^i > \frac{S}{\pi (x_{\mathrm{eh}})^2}, \tag{10}$$

where $x_{\mathrm{eh}} \triangleq v\Delta t_{\mathrm{eh}}$ denotes the distance, a vehicle would travel within the matching time at speed v, which we call the traveled matching distance; thus, $\pi(x_{\mathrm{eh}})^2$ denotes the traveled matching area. According to Eq. (10), the expected waiting time for e-hailing increases with the matching time if the ratio between the traveled area and the designated area is less than $16/\pi$ multiplied by the number of idle vehicles within that matching time; otherwise, it decreases with the matching time.

2.3 Waiting time distribution of on-street searching taxi services

For traditional on-street searching taxi services, a passenger is only likely to be spotted by an idle taxi driver when the distance separating them is close. We denote this matching area as s_{os}. For a passenger requesting service at a particular time and location, the expected total number of idle vehicles arriving within his/her matching area is given by

$$N_s = \sum_{k=0}^{N} k \frac{\exp(-s_{\mathrm{os}} N^i/S)(s_{\mathrm{os}} N^i/S)^k}{k!} = s_{\mathrm{os}} N^i/S. \tag{11}$$

Then, the probability of the existence of k idle vehicles within a matching area of s_{os} and within a waiting period of Δt is given by

$$P_t^{\mathrm{os}}\{k\} = \frac{\exp(-N_s \Delta t)(N_s \Delta t)^k}{k!}, \quad k = 0, 1, \ldots, N_s. \tag{12}$$

Then, the cumulative distribution and density function of the minimum waiting time, W, are given by

$$F_W^{\mathrm{os}}(w) = 1 - P_t\{0\} = 1 - \exp(-N_s w), \quad w \geqslant 0. \tag{13}$$

From Eq. (13), the expected waiting time for passengers with on-street searching is given by

$$\overline{w}_{\mathrm{os}} = \frac{S}{\pi (x_{\mathrm{os}})^2 N^i} + x_{\mathrm{os}}/v, \tag{14}$$

where x_t denotes the matching radius of taxis. $\Delta t_{\mathrm{os}} \triangleq x_{\mathrm{os}}/v$ is the corresponding matching time of on-street searching. From Eqs. (8) and (14), the difference in the expected waiting time between on-street searching and e-hailing services is given by

$$\Delta w = \Delta t_{\mathrm{os}} - \Delta t_{\mathrm{eh}} + \frac{1}{2v}\frac{S}{N^i \Delta t_{\mathrm{eh}} \sqrt{s_{\mathrm{os}}}}\left(\frac{2}{\sqrt{\pi}} - \sqrt{(N^i/S)\Delta t_{\mathrm{eh}} s_{\mathrm{os}}}\right). \tag{15}$$

The term N^i/S is the density of idle vehicles; thus, $(N^i/S)\Delta t_{\mathrm{eh}} s_{\mathrm{os}}$ represents the number of available idle vehicles within a passenger's matching area and matching period. For convenience, we call a passenger's matching area and matching period his/her dominant temporal-spatial area. From Eq. (15), given $\Delta t_{\mathrm{os}} = \Delta t_{\mathrm{eh}}$, i.e., the matching time of the e-haling service is equal to the searching time of on-street searching, $\Delta w > 0$ if the number of idle vehicles within a passenger's dominant temporal-spatial area is lower than $4/\pi$; otherwise, $\Delta w \leqslant 0$. In practice, one of the advantages of e-hailing services is the flexible supply of idle vehicles, which includes allowing a waiting passenger to be matched to an idle vehicle faster by e-hailing than by on-street searching. In this case, the matching time of e-hailing might be shorter than the on-street searching time, i.e., $\Delta t_{\mathrm{eh}} < \Delta t_{\mathrm{os}}$; thus, $\Delta w > 0$ always holds if the number of idle vehicles within a passenger's dominant spatiotemporal area is lower than $4/\pi$.

Based on the above analyses, we have the following proposition:

Proposition 1. Given that the matching time of e-hailing is no longer than the on-street searching time, i.e., $\Delta t_{\mathrm{eh}} \leqslant \Delta t_{\mathrm{os}}$, the expected waiting time of on-street searching is always longer than that of e-hailing if the number of idle vehicles within a passenger's dominant spatiotemporal area is lower than $4/\pi$.

From the above **Proposition 1**, we further have the necessary condition that the expected waiting time of on-street searching is shorter than that of e-hailing, which is given below:

Corollary 1. Given that the matching time of e-hailing is no longer than the on-street searching time, i.e., $\Delta t_{\mathrm{eh}} \leqslant \Delta t_{\mathrm{os}}$, if the expected waiting time of on-street searching is shorter than that of e-hailing, the number of idle vehicles within a passenger's dominant spatiotemporal area must be larger than $4/\pi$.

Therefore, when the number of idle vehicles within a passenger's dominant spatiotemporal area is low, e-hailing services can result in a shorter expected waiting time than on-street searching services. On the other hand, if there are a significant number of idle vehicles nearby, on-street searching services tend to have a shorter expected waiting time for passengers. It is important to note that the arrival rate of idle vehicles depends on factors such as the size of the vehicle fleet in the market, passenger demand, and the average duration of trips. In the next section, we relax the assumption of a fixed arrival rate of idle vehicles.

3 Passenger demand and the equilibria of markets

In this section, we further investigate the equilibria of markets for e-hailing services and on-street searching. Instead of a fixed arrival rate such as that in the last section, the number of idle vehicles is determined by the vehicle fleet size, N, the equilibrium passenger demand, q, the average trip time, T_0, and the average waiting time, w. Following that in the literature (e.g., Ke et al., 2020), we adopt the vehicle conservation conditions below[1)]:

$$N^i = N - q(T_0 + w). \tag{16}$$

For e-hailing, the trip costs for passengers include the trip fare, average travel duration, and average waiting time. On the other hand, on-street searching introduces a walking time cost, as passengers need to approach the street to hail taxis. Without loss of generality, we assume that the trip fare and average trip time are the same for both e-hailing services and on-street searching. Denote p as the average trip fare, and T_{w} as the walking time for taxi services. The generalized trip costs with e-hailing services and taxi services are given by:

$$u_{\mathrm{eh}} = \beta_1 \overline{w}_{\mathrm{eh}} + \alpha T_0 + p, \tag{17}$$

$$u_{\mathrm{os}} = \beta_0 T_w + \beta_1 \overline{w}_{\mathrm{os}} + \alpha T_0 + p, \tag{18}$$

where β_0, β_1, and α denote the values of the walking time, waiting time, and trip time, respectively. $g(\cdot)$ is denoted as the passenger demand function, which decreases with the passengers' generalized trip cost. Then, the passenger demands of e-hailing and on-street searching are given by

$$q_{\mathrm{eh}} = g(\beta_1 \overline{w}_{\mathrm{eh}} + \alpha T_0 + p), \tag{19}$$

$$q_{\mathrm{os}} = g(\beta_0 T_w + \beta_1 \overline{w}_{\mathrm{os}} + \alpha T_0 + p). \tag{20}$$

From Eqs. (19)–(20), we have the following conditions:

$$N^i_{\mathrm{eh}} = N - q_{\mathrm{eh}}\left(T_0 + \frac{1}{2v}\sqrt{S/(N^i_{\mathrm{eh}}\Delta t_{\mathrm{eh}})}\right), \tag{21}$$

$$N^i_{\mathrm{os}} = N - q_{\mathrm{os}}(T_0 + S/(\pi x_{\mathrm{eh}}{}^2 N^i_{\mathrm{os}})). \tag{22}$$

Combining Eqs. (21) and (22), we can obtain the equilibrium passenger demands and idle vehicle numbers for e-hailing services and on-street searching.

3.1 A special passenger demand function

To illustrate the above market equilibria, we assume $\Delta t_{\mathrm{os}} = \Delta t_{\mathrm{eh}}$, $T_{\mathrm{w}} = 0$ and consider a reciprocal passenger demand function, which is given by

$$g(u) = \frac{Q}{\gamma(u-\mu)}, \tag{23}$$

where Q denotes the maximum potential passenger demand, γ is a parameter reflecting the sensitivity of demand to trip cost, and $\mu = \beta_1 \Delta t_{\mathrm{eh}} + \alpha T_0 + p$. Based on Eqs. (19)–(22), the equilibrium passenger demands for e-hailing services and taxi services are given by

$$q_{\mathrm{eh}} = \frac{2vQ}{\gamma^2 \beta_1{}^2 S}\left(\sqrt{\Gamma^2 + \chi} - \Gamma\right), \tag{24}$$

$$q_{\mathrm{os}} = \frac{\pi (x_{\mathrm{eh}})^2 Q \chi}{\gamma^2 \beta_1{}^2 \Delta t_{\mathrm{eh}} S\,(\pi x_{\mathrm{eh}} \Gamma + \gamma \beta_1 S)}, \tag{25}$$

and the equilibrium idle vehicle numbers for e-hailing services and taxi services are given by

$$N^i_{\mathrm{eh}} = \frac{1}{\gamma^2 \beta_1{}^2 \Delta t_{\mathrm{eh}} S}\left(\sqrt{\Gamma^2 + \chi} - \Gamma\right), \tag{26}$$

1) It is important to note that the vehicle fleet size of a ride-sourcing platform is determined by various factors, including the platform's competition for drivers in the ride-hailing market, the drivers' income rate, and the availability of other job opportunities in the broader labor market (Bao et al., 2023). Notably, in the ride-sourcing market, where labor supply is quite flexible, the hourly income rate plays a crucial role in determining the size of the vehicle fleet (Sun et al., 2019). Additionally, the different commission fee structures employed by ride-sourcing and taxi companies have a direct effect on drivers' income and consequently, the labor supply of drivers (Angrist et al., 2021). However, this study focuses on the comparison of efficiency between e-hailing services and on-street searching with given vehicle fleet sizes. While the influence of labor supply flexibility on fleet size determination is undoubtedly an intriguing subject for future research, it falls out of the scope of this study.

$$N_{\rm os}^{i}=\frac{\chi S}{\gamma\beta_1\Delta t_{\rm eh}(\pi x_{\rm eh}\Gamma+\gamma\beta_1 S)},\tag{27}$$

where $\Gamma=Qx_{\rm eh}(T_0+\Delta t_{\rm eh})$, $\chi=\gamma\beta_1\Delta t_{\rm eh}S(\gamma\beta_1N^v-Q)$. From Eqs. (26)–(27), it can be proven that $q_{\rm eh}\geqslant q_{\rm os}$ and $N_{\rm eh}^{i}\leqslant N_{\rm os}^{i}$ hold as long as $\chi\leqslant\frac{4\gamma\beta_1S(\gamma\beta_1S+\pi x_{\rm eh}\Gamma)}{(\pi x_{\rm eh})^2}$, i.e., $Q\geqslant\frac{\gamma\beta_1\left(-4S+(\pi x_{\rm eh})^2\Delta t_{\rm eh}N\right)}{\pi(x_{\rm eh})^2(4T_0+(4+\pi)\Delta t_{\rm eh})}$. Then, we have the following proposition:

Proposition 2. Assuming that $\Delta t_{\rm os}=\Delta t_{\rm eh}$ and $T_{\rm w}=0$, the passenger demand is a reciprocal function of the generalized trip cost, as given in Eq. (23), $q_{\rm eh}\geqslant q_{\rm os}$ and $N_{\rm eh}^{i}\leqslant N_{\rm os}^{i}$ if $Q\geqslant\frac{\gamma\beta_1\left(-4S+(\pi x_{\rm eh})^2\Delta t_{\rm eh}N\right)}{\pi(x_{\rm eh})^2(4T_0+(4+\pi)\Delta t_{\rm eh})}$; otherwise, $q_{\rm eh}<q_{os}$ and $N_{\rm eh}^{i}>N_{\rm os}^{i}$.

Proof. See Appendix A.

Corollary 2. Assuming that $\Delta t_{\rm os}=\Delta t_{\rm eh}$ and $T_{\rm w}=0$ and that passenger demand is a reciprocal function of the generalized trip cost, as given in Eq. (23), e-hailing services yield greater passenger demand and fewer idle vehicles, i.e., $q_{\rm eh}>q_{\rm os}$ and $N_{\rm eh}^{i}<N_{\rm os}^{i}$, than on-street searching if $N/Q\leqslant\frac{1}{\gamma\beta_1}(4T_0/\Delta t_{\rm eh}+(4+\pi))$.

From Corollary 2, for the reciprocal passenger demand function given in Eq. (23) and with $\Delta t_{\rm os}=\Delta t_{\rm eh}$ and $T_{\rm w}=0$, the difference in passenger demand and idle vehicle number between e-hailing and on-street searching is mainly determined by the ratio of fleet size to maximum potential passenger demand, i.e., the average vehicle number per potential passenger. A larger equilibrium passenger demand indicates a higher capacity utilization rate of taxis, assuming that the average trip duration remains the same for both e-hailing and on-street searching. Therefore, e-hailing can achieve a higher capacity utilization rate of taxis compared to on-street searching if the average vehicle number per potential passenger is low. This conclusion aligns with previous research findings (e.g., Nie, 2017; Wang et al., 2020). In addition, a more extended average trip time, T_0, or a reduced matching time, $\Delta t_{\rm eh}$, will improve the chance that e-hailing will perform better than on-street searching, which is reasonable because both mean a decrease in the idle vehicle number.

3.2 Optimal vehicle fleet sizes

As demonstrated earlier, given the vehicle fleet size in the market, we can achieve an equilibrium solution for passenger demand and idle vehicle numbers. Although ride-sourcing platforms or taxi companies typically aim to maximize profits when determining fleet size, traffic planners may have different objectives, such as improving overall social welfare. Consequently, we conducted further analysis to determine the optimal vehicle fleet sizes under these two objectives. Denoting c as the unit cost of one vehicle, the profit maximization problem is given by

$$\max_{N\geqslant0}P=pq-cN,\tag{28}$$

and the social welfare maximization problem is given by

$$\max_{N\geqslant0}SW=\int_0^q g^{-1}(\omega)\,\mathrm{d}\omega+pq-cN,\tag{29}$$

where for any given N, the passenger demand, q, satisfies Eqs. (21)–(23) for e-hailing services or Eqs. (20)–(22) for on-street searching. Then, the first-order conditions of the above two maximization problems are given by

$$N\frac{\partial P}{\partial N}=N\left(p\frac{\partial q}{\partial N}-c\right)=0,\quad N\geqslant0,\quad p\frac{\partial q}{\partial N}\leqslant c,\tag{30}$$

$$\begin{gathered}N\frac{\partial SW}{\partial N}=N\left((g^{-1}(q)+p)\frac{\partial q}{\partial N}-c\right)=0,\\ N\geqslant0,\ (g^{-1}(q)+p)\frac{\partial q}{\partial N}\leqslant c.\end{gathered}\tag{31}$$

Combining Eqs. (19)–(20) with the above first-order conditions (30)–(31), we can obtain the optimal vehicle fleet sizes for the profit maximization problem and the social welfare maximization problem.

To illustrate the above profit/social welfare maximization problems to obtain the optimal vehicle fleet sizes, we further consider the cases with $\Delta t_{\rm os}=\Delta t_{\rm eh}$, $T_{\rm w}=0$, and the reciprocal passenger demand function given in Eq. (23). From Eqs. (30)–(31), we have

$$\frac{\partial q_{\rm eh}}{\partial N}=\frac{x_{\rm eh}Q}{\sqrt{\Gamma^2+\chi}},\tag{32}$$

$$\frac{\partial q_{\rm os}}{\partial N}=\frac{\pi(x_{\rm eh})^2Q}{\gamma\beta_1S+\pi v\Delta t_{\rm eh}\Gamma}.\tag{33}$$

Substituting Eqs. (32) and (33) into the first-order condition for profit maximization in Eq. (28) yields

$$N_{\rm eh}^{*}=\frac{Q}{\gamma\beta_1}+\frac{c\Gamma^2\left(4(x_{\rm eh}Q)^2-c\gamma^2{\beta_1}^2\Delta t_{\rm eh}S\right)}{\left(c\gamma^2{\beta_1}^2\Delta t_{\rm eh}S-2(x_{\rm eh}Q)^2\right)^2},\tag{34}$$

$$N_{\rm os}^{*}=\frac{Q}{\gamma\beta_1}+\frac{c(\gamma\beta_1S+\pi x_{\rm eh}\Gamma)}{\pi^2(x_{\rm eh})^4}.\tag{35}$$

The corresponding passenger demands are given by

$$q_{\rm eh}^{*}=\frac{2cx_{\rm eh}Q\Gamma}{2(x_{\rm eh}Q)^2-c\gamma^2{\beta_1}^2\Delta t_{\rm eh}S},\tag{36}$$

$$q_{\rm os}^{*}=\frac{c\pi x_{\rm eh}\Gamma+r\beta_1cS}{\pi(x_{\rm eh})^2Q}.\tag{37}$$

By substituting Eqs. (34)–(37) into vehicle conservation condition (16), the equilibrium number of idle e-hailing and on-street searching vehicles under profit maximization can be determined. Similarly, the optimization problems for maximizing social welfare can be solved.

The aforementioned analyses address the equilibrium passenger demand for a fixed vehicle fleet size, the optimal vehicle fleet size for profit maximization, and the corresponding passenger demand. Notably, ride-sourcing platforms can significantly reduce the cruising time of idle vehicles and enhance the efficiency of the ride-sourcing/taxi market through their empty vehicle repositioning guidance, particularly in scenarios characterized by uncertain demand (Guo et al., 2021) or supply-demand imbalances (Zhu et al., 2021). With repositioning strategies in place, the previous assumption of a homogeneous spatial-temporal Poisson process for idle vehicles may no longer hold. The impact of vehicle repositioning on the spatial and temporal distribution of idle vehicles is influenced by several key factors, including the platform's algorithm's effectiveness in predicting demand patterns, driver responsiveness to repositioning incentives, and the dynamic nature of the ride-sourcing market. Therefore, effectively understanding and optimizing the distribution of idle vehicles through efficient vehicle repositioning strategies represent intriguing yet challenging avenues for future research.

4 Numerical examples

In this section, we provide numerical analyses to illustrate the proposed models and the impacts of the matching time/distance on the equilibrium passenger demand and idle vehicle number. The values of the parameters are $Q = 1000$, $S = 10$, $T_0 = 0.2\ \text{h}$, $p = 2$, $c = 0.2$, $\Delta t_{\text{eh}} = 0.05\ \text{h}$, $\Delta t_{\text{os}} = 0.05\ \text{h}$, $v = 20\ \text{km/h}$, $T_{\text{w}} = 0.05\ \text{h}$, $\alpha = 10$, $\beta_0 = 10$, $\beta_1 = 30$, and $\gamma = 0.1$. The demand function is given by

$$g(x) = Q\exp(-\gamma u), \tag{38}$$

where Q denotes the maximum potential passenger demand and γ represents the sensitivity of the passenger demand to the trip cost.

4.1 Analysis of market equilibria

Figure 2 displays the number of idle vehicles and passenger demands in relation to different fleet sizes for both e-hailing and on-street searching. As expected, both the equilibrium idle vehicle numbers and passenger demand increase with the vehicle fleet size. For the same fleet size, e-hailing consistently has a significantly greater equilibrium in passenger demand than does on-street searching. In fact, the passenger demand for e-hailing services with a

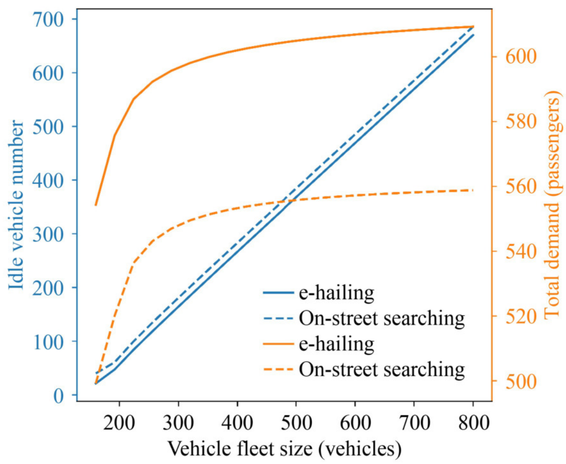

Fig. 2 Idle vehicle number and passenger demand for different fleet sizes.

200-vehicle fleet closely matches on-street searching that utilizes a fleet of 800 vehicles. This indicates that the capacity utilization rate of e-hailing surpassed that of on-street searching. On the other hand, for the same vehicle fleet size, the number of equilibrium idle vehicles for e-hailing systems is slightly lower than that for on-street searching.

Figure 3 illustrates the expected waiting time in relation to varying fleet sizes for both e-hailing and on-street searching. Notably, as the fleet size increases, the expected waiting time decreases for both modes. When evaluating the same fleet size, on-street searching tends to have a longer waiting time than e-hailing, especially for relatively small fleets. However, as fleet sizes continue to grow, e-hailing systems exhibit longer expected waiting times than on-street searching systems. This trend might be attributed to the increasing fleet size, causing a significantly reduced ratio between vehicle numbers and passenger demand in e-hailing. These observations suggest that in scenarios with high vehicle density, on-street searching could offer shorter waiting times than e-hailing, aligning with findings from the literature (e.g., Wang et al., 2020).

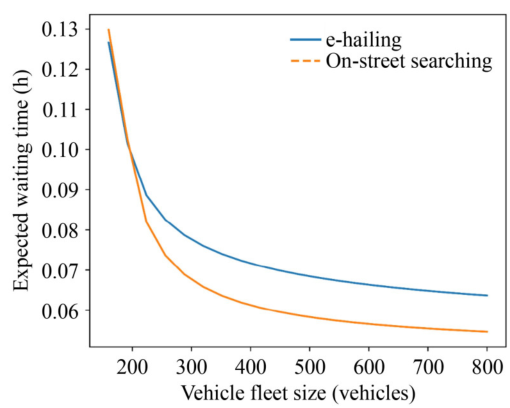

Fig. 3 Expected waiting time with different fleet sizes.

We further analyze the impacts of the matching period of e-hailing and the matching period of on-street searching (with a constant traffic speed). Figure 4 illustrates the differences in equilibrium idle vehicle numbers, passenger demands, and expected waiting times based on various combinations of matching periods for e-hailing and on-street searching. The equilibrium demand for e-hailing is generally greater than that for on-street searching, while the equilibrium idle vehicle number for e-hailing is generally lower. Only when the matching time of e-hailing is very large, approximately 7 min, does the equilibrium passenger demand of on-street searching exceed that of e-hailing. In contrast, the equilibrium idle vehicle number of e-hailing services becomes greater than that of on-street searching when both the matching period of e-hailing and the matching period of on-street searching are short. Regarding expected waiting times, e-hailing offers shorter durations than on-street searching unless the matching periods for both methods become exceptionally prolonged.

4.2 Analysis of the optimization results

Table 2 presents the results for both e-hailing and on-street searching based on optimal vehicle fleet sizes. With the aim of profit maximization, the optimal fleet size for on-street searching is slightly larger than that for e-hailing. However, e-hailing surpasses on-street searching in terms of passenger demand, total profit, and social welfare. The only areas where on-street searching performs better are the number of idle vehicles and the cumulative cruising time.

Conversely, when optimizing for social welfare, on-street searching's optimal fleet size is smaller than that of e-hailing. Nevertheless, e-hailing still outperforms on-street searching in terms of passenger demand, total profit, and social welfare. It is worth noting that the difference in the number of idle vehicles, and consequently in total cruising time, between the two modes significantly narrows.

In conclusion, our numerical analyses indicate that e-hailing generally outperforms on-street searching in terms of passenger demand and capacity utilization rate. On-street searching passenger demand may surpass that of e-hailing only when e-hailing has exceptionally long matching times. Furthermore, when optimizing for either profit or social welfare maximization, e-hailing yields greater passenger demand, overall profit, and social welfare than on-street searching.

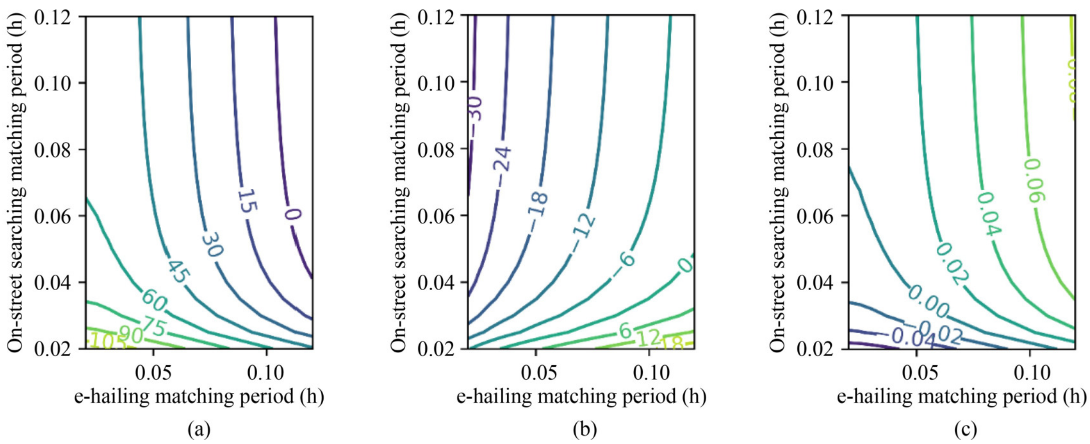

Fig. 4 Passenger demand, idle vehicle number and expected waiting time for different matching times: (a) Difference in passenger demands; (b) Difference in idle vehicle numbers; (c) Difference in the expected waiting time.

Table 2 Numerical results with the optimum vehicle fleet sizes

Result	Profit-eh	Profit-os	Social Warfare-eh	Social Warfare-os
Expected waiting time	287	249	251	215
Idle vehicle number	139	165	319	325
Total demand	594	546	603	554
Total profit	1133	1036	1116	1020
Total cruising time	157	175	331	330
Social welfare	10170	9804	10200	9835
Vehicle fleet size	276	285	452	441

5 Conclusion and future work

This study investigates the performance of e-hailing and on-street searching services based on their temporal-spatial features. By utilizing the Poisson point process to model the temporal-spatial distributions of idle vehicles, we derive the waiting time distributions and expected waiting time for passengers using on-street searching and e-hailing, respectively. The results highlight that the superiority of e-hailing over on-street searching depends on the matching time of e-hailing, the matching area of on-street searching, and the density of idle vehicles in both the matching area and period. While on-street searching services can offer shorter expected waiting times for passengers when there are a significant number of idle vehicles nearby, e-hailing services excel in rapidly pairing passengers with idle vehicles. In scenarios where the supply of idle vehicles is low, e-hailing services outperform on-street searching in terms of passenger waiting time. However, on-street searching may outperform e-hailing when the supply is relatively high.

We expand our analyses to examine market equilibria for both e-hailing and on-street searching. We outline the equilibrium conditions for a taxi market operating under e-hailing compared to on-street searching, assuming a consistent vehicle fleet size. By considering a reciprocal passenger demand function, we present a sufficient condition under which e-hailing yields higher equilibrium passenger demand and fewer idle vehicles. Our findings indicate that the performance disparity between e-hailing and on-street searching primarily depends on the ratio of the fleet size to the maximum potential passenger demand. E-hailing outperforms on-street searching when this ratio is low, indicating that a smaller average number of vehicles is available for each potential passenger. This suggests that e-hailing can achieve a greater vehicle capacity utilization rate than on-street searching when vehicle density is relatively low, corroborating previous literature (e.g., Nie, 2017; Wang et al., 2020). Additionally, increased average trip duration and reduced matching time enhance the likelihood of superior performance by e-hailing, as they both contribute to a decrease in idle vehicle numbers. Therefore, e-hailing services may prove superior to on-street searching in situations where the vehicle supply is limited or the average trip duration is prolonged.

In this paper, we assume that the distribution of idle vehicles adheres to a homogeneous Poisson process, implying uniform vehicle intensity across space and time. However, this assumption of uniformity may overlook spatial heterogeneity in vehicle supply. Furthermore, the interplay between vehicles, platform-provided vehicle repositioning, and other dynamic environments could influence the distribution of idle vehicles. Future research should explore alternative distributions that more accurately capture the uneven spatial distribution of vehicles and investigate the impact of dynamic environments on vehicle distribution. Another limitation of this study is its sole focus on a single match, neglecting the influence of unmatched vehicles from previous periods. This aspect should be investigated in future studies.

Competing Interests The authors declare that they have no competing interests.

Appendix A. Proof of Proposition 2

Proof. From Eqs. (26)–(27), we have

$$\frac{q_{\mathrm{eh}}}{q_{\mathrm{os}}} = \frac{2(\pi x_{\mathrm{eh}}\Gamma + \gamma\beta_1 S)}{\pi x_{\mathrm{eh}}\chi}\left(\sqrt{\Gamma^2+\chi}-\Gamma\right), \tag{A1}$$

Define $H(\chi)$ as:

$$H(\chi) = 2(\pi x_{\mathrm{eh}}\Gamma + \gamma\beta_1 S)\left(\sqrt{\Gamma^2+\chi}-\Gamma\right) - \pi x_{\mathrm{eh}}\chi. \tag{A2}$$

Then, $q_{\mathrm{eh}} \geqslant q_{\mathrm{os}}$ if $H(\chi) \geqslant 0$; otherwise, $q_{\mathrm{eh}} < q_{\mathrm{os}}$. Setting $H(\chi^*) = 0$ yields

$$\chi^* = \frac{4\gamma\beta_1 S\,(\gamma\beta_1 S + \pi x_{\mathrm{eh}}\Gamma)}{(\pi x_{\mathrm{eh}})^2}. \tag{A3}$$

By taking the derivative of $H(\chi)$ with respect to χ, we have

$$H'(\chi) = \frac{\pi x_{\mathrm{eh}}\Gamma + \gamma\beta_1 S}{\sqrt{\Gamma^2+\chi}} - \pi x_{\mathrm{eh}}. \tag{A4}$$

Substituting Eq. (A3) into Eq. (A4), we have $H'(\chi^*) < 0$. As $H'(0) > 0$, $H(0) = 0$, and $H'(\chi)$ decrease with χ, we have $H(\chi) \geqslant 0$ for $\chi \leqslant \chi^*$ and $H(\chi) < 0$ for $\chi > \chi^*$. From the definition of χ, we have

$$\gamma\beta_1 \Delta t_{\mathrm{eh}} S\,(\gamma\beta_1 N^v - Q^*) = \frac{4\gamma\beta_1 S\,(\gamma\beta_1 S + \pi x_{\mathrm{eh}}\Gamma)}{(\pi x_{\mathrm{eh}})^2}. \tag{A5}$$

Solving Eq. (A5) yields

$$Q^* = \frac{\gamma\beta_1\left(-4S + (\pi x_{\mathrm{eh}})^2 \Delta t_{\mathrm{eh}} N^v\right)}{\pi (x_{\mathrm{eh}})^2 (4T_0 + (4+\pi)\Delta t_{\mathrm{eh}})}. \tag{A6}$$

As χ decreases with Q, $\chi \leqslant \chi^*$ means $Q \geqslant Q^*$. Thus, $q_{\mathrm{eh}} \geqslant q_{\mathrm{os}}$ if $Q \geqslant Q^*$; otherwise, $q_{\mathrm{eh}} < q_{\mathrm{os}}$. Similarly, we can prove that $N_{\mathrm{eh}}^{iv} \leqslant N_{\mathrm{os}}^{iv}$ if $Q \leqslant Q^*$; otherwise, $N_{\mathrm{eh}}^{iv} > N_{\mathrm{os}}^{iv}$. This completes the proof.

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