RESEARCH ARTICLE

Review of studies on taxi mobility and e-hailing taxi service

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Abstract: Taxi mobility has lately been a popular subject of research in geography, physics, complex network science, and computer science. Prevalent studies have focused on spatio-temporal variations in taxi mobility and operational strategies for taxis. However, with the advent of e-hailing taxi services, a growing number of scholars have attempted to uncover the impacts of this emerging mode of travel on human mobility and urban dynamics. For example, some researchers have studied taxi market equilibrium after the emergence of e-hailing services whereas others have focused on comparing differences in taxi pricing strategies and policies between the traditional taxi market and e-hailing services. In this article, we systematically review research on taxi mobility and the impacts of e-hailing services on the traditional taxi market. Further research is needed to develop a better understanding of taxi mobility and e-hailing services..

Keywords: e-hailing service, taxi market, human mobility, operation strategy, subsidy policy

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1 Introduction

With the rapid development of Information and Communication Technologies (ICT), a growing amount of data on the trajectory of taxis have become available that pose new challenges and provide novel opportunities for urban research. Taxi trajectory data usually record such information as the location, time stamp, angle, and velocity of the vehicle. Taxi pick-up and drop-off locations can be extracted from GPS trajectory data that reflect accurate information about the origins and destinations of passengers. As such, GPS-equipped taxis can be viewed as pervasive sensors[1], and large-scale GPS traces can help to reveal urban social dynamics[2].

The traditional mode of taxi service requires passengers to hail taxis on the roadside. In this way, taxis are often difficult to reach during rush hours, bad weather, and holidays, and customers may be refused by cabdrivers. With the emergence of the e-hailing services, the traditional taxi market has greatly changed. In 2009, Uber in the United States began to provide e-hailing services. Two major Chinese transportation network companies, Didi and Kuaidi, launched a nationwide subsidy war in 2014 that signaled the official advent of e-hailing in people's daily lives. Users of e-hailing services in China in 2014 had reportedly increased by 559.4%[3].

The difference between an e-hailing service and the traditional taxi service is that taxi drivers and passengers can be directly connected through third-party mobile phone applications in the former. Passengers can request taxi services through mobile phone applications, and taxi drivers can obtain information on the passenger's origin and destination in advance. Emerging e-hailing services have greatly improved people's experience of taxi travel. Nevertheless, we need to consider some issues, such as people without smartphones and older residents finding it more difficult to obtain taxi services. In addition, the surge pricing phenomenon, long work hours, safety, and market competition are also subjects of concern.

This article systematically reviews research on taxi mobility and the impacts of e-hailing services on the traditional taxi market. It is worth noting that we discuss only e-hailing taxi services and traditional taxi services. Ride sourcing (a mode in which private cars provide travel services) and other modes of shared mobility are beyond the scope of this article.

The remainder of this paper is organized as follows: Section 2 reviews studies on taxi mobility from two aspects: the spatio-temporal variation in taxi mobility and operational strategies of taxis. Section 3 introduces literature on the impacts of e-hailing services on the traditional taxi market from the perspectives of taxi market equilibrium, pricing strategy, and subsidy policy. The last section offers a summary and discussion of directions for future research.

2 Taxi mobility

With the rapid development of location acquisition technologies [4], a growing number of scholars have begun studying location data with spatio-temporal information. The large volume of taxi trajectory data is suitable for examining taxi mobility patterns. In general, the literature has analyzed taxi mobility from two aspects: the spatio-temporal variation in taxi mobility and the operation strategies of taxicabs.

2.1 Spatio-temporal variation in taxi mobility

Human movements are not randomly distributed but follow reproducible patterns [5]. As shown in Table 1, researchers have modeled taxi trajectories in many cities and found that the taxi trip distance follows an exponential distribution [?]. In addition, the duration of a taxi trip follows a power law distribution [11]. Jiang et al. [12] created a dataset based on information from 50 taxis during a six-month period in Sweden, and observed that taxi trip distance follows a bipartite power law distribution. By analyzing the trajectory of 15,000 taxis, Peng et al. [8] found that people travel for three main purposes during the working day: commuting between workplaces and residences, moving between workplaces and entertainment places, and almost all travel flows between locations can be regarded as the linear superposition of the above three travel flows.

Table 1. The displacement distributions of human travel by taxi.

Data	Distribution	Literature
Taxi trajectory data from June 1, 2009 to June 7, 2009 in Shanghai, China	Exponentially truncated power law with the scaling exponent $\beta = 1.2 \pm 0.15$	Liu et al. [6]
Taxi trajectory data from October 1, 2008 to November 30, 2008 in Beijing, China	Exponential distribution	Liang et al. [7]
1.58 million taxi trips in Shanghai, China	Exponential distribution	Peng et al. [8]
Taxi trips from four major cities (Beijing, Tianjin, Shanghai, and Nanjing) in China and the San Francisco Bay Area in the United States	Exponential laws distribution	Wang et al. [9]

Taxi trajectory reflects the characteristics of human movement and the spatio-temporal distribution of human activities. In addition, this kind of data are suitable for extracting urban events with high accuracy [?]. Chen et al. [15] found frequent trajectories between given start and end points. Liu et al. [16] used the k-means clustering algorithm to reveal the temporal and spatial preferences of high-income and average-income taxi drivers in Shenzhen. Liu et al. [17] studied the time variation of taxi pick-up and drop-off locations, and identified six "source-sink" areas related to land use types. Hu et al. [18] investigated the distribution of activities of urban taxi drivers, and Chen et al. [19] found that taxi demand in peripheral areas decreased significantly under increasing precipitation during non-rush hours, while during rush hours, the demand for highly profitable taxi services increased significantly. Qian and Ukkusuri [20] analyzed factors affecting taxi pick-up and drop-off locations by implementing a geographically weighted regression model. Dong et al. [21] compared taxi trip records and Internet-based ride-sharing trip records provided by the DiDi company, and discovered that the demand for ride-sharing trips increased in hot areas and during peak hours. Zhu and Guo [22] proposed a location-specific time series decomposition and outlier detection approach to detect urban events using taxi OD data. Chawla et al. [23] proposed a two-step mining and optimization framework for inferring the root cause of anomalies in road traffic data. Zhang et al. [14] extracted the dynamics of human flow from taxi traces for detecting social events and evaluating their impacts. Chen et al. [24] proposed the iBOAT algorithm to detect anomalous taxi trajectories.

2.2 Operation strategy

Another strand of studies has emphasized the operation strategies of taxis. An important question for these strategies pertains to where to search for passengers by cruising. The literature has developed several customer-searching strategies based on time-series-based prediction, [25] detection of hotspots of travel demand [26], the logit model [?], and the historical performance of cabdrivers [29]. If one does not cruise, where does one wait for passengers? Li et al. [29] discovered that high-income taxi drivers usually adopt a hunting strategy and ordinary-income taxi drivers use a waiting strategy. In addition, they suggested that waiting is a better strategy during rush hours. Yuan et al. [30] proposed an algorithm to detect good parking places with a high probability of getting a customer, short waiting time, and long distance for the next trip.

The collective operation strategy of taxi drivers is another topic of interest. Kang and Qin [31] studied the operational preferences of taxis in Wuhan and extracted six major patterns using non-negative matrix factorization. Hu et al. [18] found that the area where cabdrivers were generally idle was close to their last drop-off location by calculating the distance between the average center of the pick-up location and that of the drop-off location. Dong et al. [32] divided taxis into three categories according to daily income, and compared differences among three groups from the perspectives of spatio-temporal pattern and operational strategy. Their conclusions showed that high-income drivers tended to complete as many trips as possible, and covered longer trip distances. Liu et al. [16]

also investigated different operational strategies used by high income drivers and ordinary-income drivers.

Other scholars have focused on the question of how to dispatch taxis to improve operational efficiency. Vazifeh et al.[33] provided a network-based solution to address the minimum fleet problem, and reported that their method led to a 30% reduction in fleet size compared with taxi operations at the time in the city of New York. Gao et al.[34] optimized taxi driving strategies based on the Markov decision process using taxi trajectory data in Beijing. Ma et al.[35] developed a mobile cloud architecture-based taxi-sharing system that accepts customers' real-time ride requests and schedules taxis to pickup them. Zheng and Wu[36] proposed a stable marriage approach to solve the problem of non-sharing taxi dispatches and modeled the problem of sharing taxi dispatches by solving a maximum set packing problem. Zhan et al.[37] implemented a bipartite graph approach to model the taxi dispatching problem. Their method reduced 60%–90% of the total cost of empty trips, and only one-third of all taxis were needed to serve all trips in an example of taxi trips in New York City. Gao et al.[38] proposed a mobile taxi-hailing system by considering the net profits of all taxis, waiting times of passengers, different taxi resource configurations, and the cost of cruising distances for taxis.

3 Impacts of e-hailing services on traditional taxi market

The emergence of many transportation network companies, such as Didi and Kuaidi in China, and Uber and Lyft in the US, has significantly facilitated human mobility, and the services provided are convenient and efficient. In particular during rush hours and on rainy days, people no longer need to hail taxis on streets. Customers can release travel demands on mobile applications in advance, and taxi drivers can immediately obtain this information for nearby customers directly through the application. Emerging e-hailing services facilitate communication between customers and drivers, and thus has induced many scholars to study this mode of travel. Given the fierce competition among e-hailing apps, understanding the mechanism of e-hailing services and revealing their effects on the traditional taxi market is meaningful in theory and significant in practice.

3.1 Taxi market equilibrium

Taxi market equilibrium is an issue that many researchers have studied. Yang and Wong[39] proposed a network model to analyze traditional roadside-hailing taxi services, and found that the average taxi utilization decreased sharply with the increase in fleet size, and that the higher taxi utilization is, the larger is the average customer waiting time. They extended this model by incorporating demand elasticity and road congestion[40], market competition and regulation[41], multi-period dynamic taxi services with endogenous service intensity[42], and multiple user classes and multiple vehicle modes into it[43]. Moreover, Wong et al.[44] proposed a cell-based model to describe the movement of customers to search for taxis that incorporates the logit-based search model and the intervening opportunity model. This model can be used to predict the effects of adjusting the size of the taxi fleet and customer travel demand on the distance and time for which the customer needs to search.

Due to the emergence of e-hailing applications, the interactions between taxi drivers and customers have become more complex. Considering e-hailing, He and Shen[45] first modeled the interaction between customers and taxi drivers at taxi market equilibrium under a hybrid of the e-hailing mode and the roadside hailing mode. They adopted a network model that considers the spatial distribution of demand, and examined the choice of mode and taxi movements at network equilibrium under any given pricing strategy of the e-hailing platform. However, they failed to explicitly consider the pricing strategy of a taxi hailing apps in the analysis. A later study conducted by Wang et al.[46] investigated the pricing strategies of a taxi hailing platform in the context of overall taxi market equilibrium. Their results indicated that if the platform's charge on one side is increased while that on the other side remains unchanged, the demand for e-hailing services decreases, and if the charge on one side is increased while that on the other side is reduced by the same amount, the demand either increases or decreases. Qian and Ukkusuri[20] modeled the taxi market as a "multiple leader-follower game" at the network level and analyzed the equilibrium of the taxi market with competition between traditional taxi services and e-hailing services. Their results indicated that the fleet size and pricing policy are closely related to the level of competition in the taxi market, and competition has a significant impact on overall travel costs for the passenger, customer waiting times, and overall taxi utilization.

3.2 Pricing strategy and subsidy policy

Taxi pricing strategies have garnered the interest of many researchers. Salnikov et al.[47] compared the cost between Yellow Cab and Uber X, which is the cheapest version of the Uber taxi, in New York City. They observed that a Yellow Cab ride appeared on average 1.4 US dollars cheaper than Uber X, whereas Uber X became cheaper only above a threshold of 35 dollars. However, another study by Noulas et al.[48] showed that the Uber X service appeared considerably cheaper than Black Cab in London. Interestingly, Uber X was much cheaper in London than in New York. Another key issue in e-hailing apps is the surge pricing phenomenon: The price of a trip fluctuates with time and varies from one area to another in a city. For example, prices can reach 7.5 times the base rate on New Year's Eve[49]. Previous studies have shown that a majority of surge pricing lasts less than 10 minutes, and surge prices have a strong negative impact on passenger demand and a weak positive impact on car supply[50]. Chen[51] also reported that surge pricing increased the supply of Uber rides. Noulas et al.[52] reported that surge pricing was the main factor causing the higher fees for Uber X in New York.

Subsidy policy is usually a way for transportation network companies to attract users. For example, competition among e-hailing service companies, e.g., Didi and Kuaidi, triggered a fierce subsidy war from January to August of 2014 in China. The two companies offered promotion fees to taxi drivers using their apps to serve passengers. Meanwhile, they gave subsidies to passengers who used their apps to hail taxis. Passengers and drivers could get 5 to 20 RMB for each e-hailing order. Table 2 shows the specific amounts of subsidies distributed to drivers and customers in different periods of the subsidy war. The growth rate of users of e-hailing services reached 559.4% in 2014, compared with the number in 2009[3].

Table 2. Subsidy policies in different periods during the subsidy war (Unit: RMB Yuan)[54].

Duration	Didi		Kuaidi	
	Driver	Customer	Driver	Customer
Before Jan.9th	0	0	0	0
Jan. 10th -Feb.16th	10	10	10	10
Feb. 17th -Mar. 4th	10 (50 for new user)	10–20	5–11	10–13
Mar. 22nd-May 16th	10	3–5	5–11	3–5
May 17th -July 8st	10	0	5–11	0
After Aug. 10th	0	0	0	0

Few studies have drawn attention to the effects of subsidy policy. An empirical study conducted by Leng et al.[53] showed that when the subsidy war in China was raging, the average number of trips per taxi increased, average idle time of taxicabs decreased, and the number of short-distance trips increased. But the spatial distribution of pick-up and drop-off hotspots did not change significantly. Su et al.[54] observed that changes in pick-up and drop-off locations varied greatly in quantity and spatial distribution during the subsidy war. A later study conducted by Fang et al.[55] found that distributing a larger amount of subsidy to taxi drivers and customers can help improve the efficiency of searching customers. In other words, it can reduce the idle times and distances of taxis. The zones of operation of taxi drivers in Shenzhen changed greatly during the subsidy war. From the perspective of urban equity, in Su et al.'s[56] study, the subsidy war finally mitigated the inequality among taxi services in the inner city, but aggravated that in the outskirts. Wen et al.[57] evaluated the difficulty of taking a taxi under different subsidy programs, and observed that it was difficult to hail a taxi if customers obtained subsidies. However, this difficulty could be alleviated if transportation network companies gave subsidies to taxi drivers.

4 Conclusions

Taxi mobility is an important subject of research in geography, physics, complex network science, and computer science. Understanding the spatio-temporal variation in taxi mobility and their operational strategies are important for urban planning and traffic management. The emergence of e-hailing services poses challenges and opportunities for research on taxi mobility. Although the research has discussed the impact of the emergence of e-hailing taxi services on the traditional taxi market from the perspectives of taxi market equilibrium, pricing strategy, and subsidy policy, many unresolved issues need further discussion.

First, what is the difference between the operational patterns of e-hailing taxis and traditional taxis? Taxi drivers often provide both e-hailing and traditional taxi services. Drivers who provide traditional taxi services usually cruise on the road or stay in specific locations to look for passengers. However, drivers who use e-hailing apps may take an order and drive to the passenger's location. Is there a transition between these modes for the individual driver? And to what extent does the e-hailing service change the cabdriver's operational efficiency? These are questions that have not yet been answered.

Moreover, what is the impact of the e-hailing services on the sustainable development of the city? Energy conservation and emissions reduction have long been significant themes of urban governance. Can e-hailing taxis help reduce emissions compared with traditional taxis? How do e-hailing taxis affect traffic congestion? In addition, as far as social justice issues are concerned, how do we deal with the unfair treatment of special people (e.g., older citizens and people do not have smartphones) by e-hailing taxi services?

Finally, the competition and complement among e-hailing taxi services, traditional taxi services, and other forms of public transport need to be further explored. Understanding the interactions among these modes of transportation is important for urban planning and management. The knowledge obtained from this can help the taxi management authorities to develop precise and targeted management tactics for e-hailing services.

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